ABSTRACT

Title of Dissertation:	REVOLUTIONIZING RETAIL: THE IMPACT OF TECHNOLOGY STRATEGIES ON OPERATIONAL PERFORMANCE
	Ruifeng (Brett) Wang, Doctor of Philosophy, 2025
Dissertation directed by:	Professor Martin Dresner, Department of Logistics, Business, and Public Policy

This dissertation comprises three chapters, each focusing on a different technology used to facilitate operations and performance in the retail industry.

In the first chapter, I examine virtual try-on (VTO) technology in the eyewear industry. VTO has gained traction among both pure online and dual-channel retailers. My results indicate that VTO significantly improves overall performance, particularly benefiting dual-channel retailers. This unexpected result is likely due to the facilitation of webrooming, where shoppers research products online but make purchases offline. VTO, thus, helps retailers to retain webrooming customers, mitigating the risk of lost sales to competitors. Furthermore, this study highlights the contributions of VTO to retailer resilience during unexpected disruptions. These findings underscore VTO's role as a critical tool for maintaining business continuity.

The second chapter explores mobile consumer scanning technology (MCST) for grocery retailers. Using traffic and sales data, I examine the impact of MCST on in-

store customer dwell time, average transaction size, and number of customer visits. The findings reveal that MCST leads to a reduction in in-store dwell time. Moreover, the technology results in increased customer visits. However, MCST also leads to a decrease in spend per shopping visit, as the technology allows customers to track spending as they shop. Extended analyses further reveal that MCST alters daily shopping patterns and increases retailer's sales volume. These findings advance the literature on the application of consumer-centered retail technologies, highlighting both theoretical and managerial implications from the implementation of MCST.

The last chapter focuses on design technologies for furniture retailers. Fit risk significantly impedes furniture sales, since consumers may be reluctant to purchase furniture if they are unsure how it will fit into their homes. Retailers use pre-sales practices, like room planners, augmented reality (AR) technology, and online (human) interior designers to mitigate fit uncertainty. Post-sales practices, in particular, lenient return policies, further address fit concerns. Analyzing data from 102 U.S. furniture retailers over five years, I find that pre-sales and post-sales practices independently enhance sales performance but often act as substitutes. Moreover, extended analysis reveals complex interactions among the pre-sales and post-sales practices in producing online and offline sales.

REVOLUTIONIZING RETAIL: THE IMPACT OF TECHNOLOGY STRATEGIES ON OPERATIONAL PERFORMANCE

by

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Preface

Retailers today navigate an increasingly complex environment marked by shifting consumer behaviors, intensifying competition, and rapid technological advancements. This dissertation investigates how retailers strategically leverage cutting-edge technologies to enhance operational efficiency, foster customer engagement, and elevate overall business performance. Structured into three distinct yet interconnected chapters, each segment provides insights into specific retail technologies, yielding crucial implications for both scholarly research and industry practice.

The first chapter explores virtual try-on (VTO) technology within the eyewear retail sector. Empirical findings from this study reveal that VTO substantially enhances retailers' sales performance, particularly benefiting dual-channel retailers that operate both online and offline sales channels. Central to this enhancement is VTO's role in facilitating webrooming behavior, which effectively reduces consumer defection to competitors after initial online product exploration. Moreover, the research underscores how VTO acts as a significant driver of retailer resilience, enabling businesses to maintain stable performance levels and swiftly recover in the face of unforeseen disruptions such as market shocks or logistical issues.

This chapter contributes to the literature by providing empirical validation of VTO's multifaceted role, not only as an effective tool for consumer decision-making but also as a strategic asset in strengthening retailer resilience. Academically, it enriches the discourse on multichannel retailing, clarifying how innovative consumer-interfacing technologies can be harnessed to enhance sales performance. Practically, it offers actionable guidance for retail managers on effectively implementing VTO, emphasizing its strategic importance in enhancing consumer engagement and sustaining operational continuity during disruptions.

The second chapter shifts the analytical lens to mobile consumer scanning technology (MCST), predominantly employed by grocery retailers. Utilizing store traffic and sales data, the chapter reveals significant behavioral adjustments among consumers using MCST, specifically characterized by shorter in-store visits and increased shopping frequency. These shifts are driven largely by the convenience and immediacy offered by the technology. Importantly, the chapter identifies price transparency facilitated by MCST as a key factor altering consumer purchase behavior, reducing spending per transaction yet driving a notable increase in overall transaction frequency, ultimately boosting total sales.

This chapter contributes to the understanding of consumer logistics technology adoption, especially regarding behavioral economics concepts like mental accounting and consumer spending adjustments driven by increased transaction transparency. Practically, it provides retail managers with nuanced insights into how MCST affects shopping patterns, enabling more informed decisions about technology deployment strategies aimed at maximizing revenue. Additionally, it highlights how retailers can leverage MCST to enhance consumer satisfaction and loyalty through greater convenience and transactional transparency.

The third chapter examines the impact of design-related technologies within the furniture retailing context, addressing consumers' primary concerns about product fit. Drawing from data spanning five years from 102 U.S. furniture retailers, the chapter systematically evaluates pre-sales practices, such as room planner, augmented reality technology, and online design consultations, as well as post-sales practices like lenient return policies. The findings indicate that both pre- and post-sales practices independently bolster sales performance, yet interestingly, they also demonstrate substitution effects when implemented concurrently. Further, detailed analysis reveals nuanced interactions among these technologies, demonstrating differential impacts on online versus offline sales channels.

This chapter significantly advances theoretical understanding by clarifying the interplay and substitutability among pre-sales and post-sales practices in a complex retail environment. It adds depth to existing knowledge regarding how pre- and post-sales practices complement or substitute with each other, shaping consumer purchasing decisions. From a practical standpoint, these insights guide retailers in strategically selecting and integrating pre-sales and post-sales practices to enhance sales performance across channels.

Collectively, these chapters deepen the understanding of retail technology's transformative potential, providing essential frameworks and evidence-based insights for retailers aiming to optimize performance, manage consumer expectations, and sustain a competitive advantage in a rapidly evolving market landscape.

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Chapter 1: Eying Sales Gains with Virtual Try-on Technology: A Comparison between Dual-channel and Pure Online Retailers

1. Introduction

The retail industry has undergone dramatic transformations in recent decades due, largely, to the development of e-commerce. According to the U.S. Census Bureau, the proportion of e-commerce retail sales to total sales in the U.S. grew from 0.8% in 2000 to 14.3% in 2022.[1] Online shopping has become a popular alternative to traditional, offline shopping (Chen et al. 2008). According to Statista, 80% of U.S. consumers shop online with more than 55% preferring online shopping over offline shopping. Moreover, 74% of consumers state that they search online before visiting physical stores (Brophy 2023). Given the availability of both online and offline shopping options, many shoppers engage in comparative evaluations of products and prices across channels, with the goal of identifying superior products and favorable deals (Aw 2020).

Given the competitive operating environment, retailers have searched for ways to improve the customer experience, including the adoption of new technologies, while integrating online and offline shopping channels (Rooderkerk et al. 2023). Roggeveen and Sethuraman (2020) define retail technologies to include applications, devices, tools, techniques, models, and enablers that utilize engineering, analytics, or

[1] https://fred.stlouisfed.org/series/ECOMPCTSA (Accessed in January 2023)

digitization. One such technology is the virtual try-on (VTO) application. VTO, based on augmented reality (AR) and virtual reality (VR), is a technology that manipulates products via digital devices to simulate the “try-on” experiences with physical products (Fiore and Jin 2003). The technology allows online shoppers to virtually try on products, reducing purchasing uncertainty and enhancing the customer experience (Brady 2022).

VTO technology has been widely adopted in several product categories, including eyewear, cosmetics, jewelry, and shoes (Bonetti et al. 2018; Kim and Forsythe 2008; Pantano et al. 2017). VTO is attractive to retailers for at least two reasons: First, it can expand market demand by providing an innovative, interactive way for customers to explore products, therefore making online shopping more accessible (Brady 2022). Second, VTO can increase the customer conversion rate (i.e., shopper to purchaser) through its delivery of detailed visualizations, thus reducing uncertainty about product features and increasing consumer confidence (Bonetti et al. 2018; Kim and Forsythe 2008; Kumari and Bankar 2015). Overall, VTO fosters an interactive relationship between retailers and customers, improving retailer performance by enhancing communication, reducing transaction costs, and enriching the customer experience.

Although VTO may be most associated with online shopping channels, it can also be used as a component of a multichannel retailing strategy. The technology can support a retailer’s online channel by substituting for actual try-on experiences at physical stores, thus allowing online customers to try on and purchase products without making physical store visits. However, VTO can also complement offline channels.

Customers can use VTO as an initial try-on experience, narrowing their product choices before visiting a physical outlet to finalize their purchase.

The process of first searching for products online but then purchasing offline is often termed "webrooming". Webroomers can leverage online product information to enable their offline purchases. Customers can gain valuable product information online and then take advantage of additional services from customer representatives in physical stores, while reducing shipping time and costs (Flavián et al. 2016; Jiao and Hu 2022; Kumar et al. 2017). As a result, VTO may act as a complement to physical retail channels, facilitating online searches for eventual offline purchases. The goal of this paper is to examine the impact of VTO on retail sales, most importantly to determine the substitutability or complementarity of VTO to offline sales channels.

The setting for this analysis of VTO's impact on retail sales is the U.S. eyewear industry. Retailers in this industry sell (mainly) prescription eyeglasses, including frames and customized lenses. Eyeglass retailers may operate as pure online retailers or as dual-channel (online and offline) retailers.[2] Pure online retailers employ VTO to enhance online sales, while dual-channel retailers may employ VTO to enhance both online and offline sales. If VTO is a substitute for physical try-on facilities, dual-channel retailers may sacrifice offline sales for online sales after implementing the technology. Moreover, the expectation would be that pure online firms can achieve greater sales benefits (in percentage terms) from employing VTO compared to dual-channel firms. However, if VTO is a complement to offline channels, then dual-channel

[2] There are also pure offline retailers, but I do not consider these retailers since they generally do not have websites with VTO technology.

firms may experience higher benefits from this technology employment compared to pure online firms.

This analysis is conducted using a dataset from the eyewear industry compiled from multiple sources. I construct a sample from 30 eyewear retail chains in the U.S. that operate online only or both online and offline channels. Data collected include consumer spending data, information on the employment of VTO technology, the availability of an offline channel, and market-level demographics. I first estimate the overall business value of VTO on retail sales and then analyze the differential impact of VTO for pure online and dual-channel retailers.

The results first verify the business value from VTO demonstrating its positive impact on retail sales. Specifically, employing VTO increases a retailer's sales by an average of 33.1%. Further, I show that dual-channel retailers derive greater benefits from VTO than pure online retailers (Flavián et al. 2016). In addition, I find that dual-channel retailers experience higher offline sales (as well as online sales) after employing VTO technology, an indicator of potential webrooming behavior. In sum, I find that the use of VTO benefits both pure online and dual-channel retailers, showing the business value of the technology. Moreover, VTO enhances offline channel sales, as well as online sales, for dual-channel retailers, highlighting the ability of VTO to contribute to a multichannel strategy.

As a robustness check on my results, I conduct a novel experiment leveraging the closure of offline channel outlets during the COVID-19 pandemic. With offline purchases restricted due to store closures, I demonstrate that retailers that employed VTO technology experienced a greater increase in online sales compared to retailers that did not employ the technology, a further demonstration of the business value of VTO. Moreover, the increased sales were higher for dual-channel retailers that employed VTO, compared to pure online retailers that also employed VTO, further demonstrating the additional value of this technology to dual-channel retailers (i.e., the potential webrooming effect).

This study makes three theoretical contributions. First, I enrich the literature on customer-interfacing retail technologies by exploring the impact of VTO technology on sales performance across retail channels. Building upon foundational research (Grewal et al. 2020; Roggeveen and Sethuraman 2020; Sethuraman and Parasuraman 2005), I extend the understanding of how VTO enhances retail sales performance, particularly on how it complements offline sales channels. Second, this research contributes to the understanding of channel capabilities, a concept extensively examined in the literature (Avery et al. 2012; Bang et al. 2013; Wang and Goldfarb 2017). I focus on how customer-interfacing technologies, such as VTO, enhance both online and offline sales channels. Finally, I explore how VTO may lead to consumer webrooming. Webrooming has become a vital component of shopping practices in a multichannel retail environment, enhancing the search process, reducing purchase uncertainty, and improving customer satisfaction (Flavián et al. 2016; Jiao and Hu 2022).

In summary, this study reveals that VTO significantly influences both online and offline sales. By enhancing online capabilities, VTO increases online sales, but it also improves the ability of retailers to market products in an offline environment.

VTO, thus, may both replace and supplement physical try-on facilities available in offline locations.

This research highlights key managerial implications of VTO technology in the retail sector. First, my study demonstrates the business value of VTO in that its employment significantly increases retail sales performance. This innovative technology allows customers to try on products virtually, encouraging transactions and sales. Second, dual-channel retailers can leverage VTO to boost offline sales by encouraging webrooming behavior, preventing customers from migrating to competitors' offline channels. Combining VTO with a multichannel strategy helps retain customers across both online and offline sales channels. Finally, dual-channel retailers with VTO gain a competitive edge during unforeseen disruptions, such as the COVID-19 pandemic. By offering services across online and offline channels, VTO employment helps ensure the continuity of business operations while mitigating risks. Retailers may invest in VTO to act as strategic "insurance" against market uncertainties since the technology supports both online and offline channels.

2. VTO in the Eyewear Industry

VTO technology has gained popularity across several retail sectors, such as apparel (Kim and Forsythe 2008) and eyewear (Bonetti et al. 2018; Pantano et al. 2017). The technology allows retailers to create virtual models based on a customer's facial characteristics, body shape, and other measurements (Kim and Forsythe 2008). Shoppers can utilize VTO to visualize the look and fit of items, such as dresses and eyeglasses, offering a digital alternative to traditional fitting rooms (Bonetti et al. 2018; Kim and Forsythe 2008; Kumari and Bankar 2015).

Figure 1 provides a screenshot of VTO technology from an online eyewear retailer. To access VTO, shoppers either capture a photo or upload a photo to the retailer's website. The technology can then automatically detect the positions of the user's eyes or be manually adjusted to capture these facial features. Subsequently, the technology overlays images of selected eyeglasses onto the customer's face, demonstrating and customizing product look and fit (Yuan et al. 2011).[3]

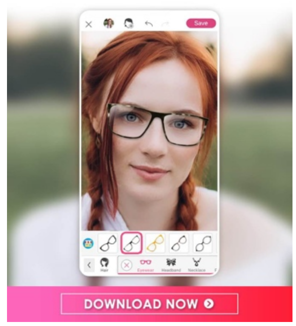


Figure 1. Example of Virtual Try-On at an Eyewear Retailer[4]

Industry surveys reveal high customer satisfaction with VTO technology. A survey conducted by Vertebrae, a provider of AR technology solutions, found that eight of ten shoppers expressed an interest in using VTO if it were readily available on a website or on a mobile application (Brady 2022). Moreover, the survey found that 70% of individuals who used VTO reported that their experience contributed to a product purchase.

Although VTO is used across various industries, I have selected the eyewear sector as my research setting for three reasons: First, VTO technology has matured

[3] A limitation of this technology is that the generated photo can only be viewed from the front. Emerging 3D VTO technologies feature 3D photos that allow customers to view their photos from different angles.

[4] https://www.perfectcorp.com/consumer/blog/selfie-editing/best-glasses-try-on-app-ios-android (Accessed in January 2023)

significantly within the eyewear retail industry, having been in use for over a decade (Santini 2013). A 2019 Gartner survey reported that 46 percent of eyewear retailers have adopted or planned to implement augmented reality (AR) solutions, including VTO technology before 2021 (Omale 2019). Moreover, a customer survey reported that eyewear is the product category in which shoppers find VTO to be most useful (Brady 2022). Second, the implementation of VTO in the retail eyewear industry varies across retail chains and over time within chains, providing an opportunity to assess the impact of VTO on sales performance against an industry control group. Lastly, the eyewear retail industry is characterized by well-established pure online retailers and dual-channel retailers. This diversity allows for a comprehensive analysis of VTO's impact on both online and offline consumer shopping behaviors.

3. Literature Review

There are three streams of literature that are relevant to my study: Customer-interfacing retail technology, retailer channel capabilities, and consumer research shopping.

3.1. Customer-Interfacing Retail Technologies

Customer-facing technologies in retail are evaluated and classified based on distinct criteria, integral to understanding their impact on the sector. These criteria are: (1) cost-saving or service enhancement, detailed by Sethuraman and Parasuraman (2005); (2) convenience and social presence, explored by Grewal et al. (2020); and (3) influence on the shopping and purchasing processes, as delineated by Roggeveen and

Sethuraman (2020). Each framework provides a unique lens through which the potential of these technologies can be assessed.

Sethuraman and Parasuraman (2005) classified the technologies as primarily cost-saving or service-enhancing. They defined retailer costs as expenses related to making the product available for sale to end consumers, including product acquisition, delivery, inventory, and ordering. They defined services as a variety of non-price store attributes (e.g., location, product assortment, and sales assistance), supplementary services, and convenience aspects that contribute to the overall customer experience. Within this categorization, VTO can be considered a technology that primarily enhances customer service.

Grewal et al. (2020) described the features of customer-interfacing technologies through two dimensions, convenience and social presence. The convenience of a technology is represented by the benefits experienced from its use, such as the ability to access product information from QR codes. Social presence connotes how well the technology can mimic the human dimension, such as the ability of chat boxes to substitute for human customer service representatives. As a technology, VTO provides aspects of both convenience and social presence.

Roggeveen and Sethuraman (2020) classified customer-interfacing retail technologies according to the ability of the technology to facilitate the shopping and purchasing processes. Technologies can be used to generate customer needs, facilitate searches, ease the purchase process, aid in shipping and delivery, and/or contribute to follow-up services and loyalty management. VTO's main purpose is to facilitate the search process.

The evolution of customer-facing technologies has garnered considerable attention in academic research, encompassing a range of applications from consumer self-ordering and self-checkout systems to e-service delivery systems. For example, Kang et al. (2024) studied self-ordering systems in omnichannel services. Using queuing theory, they found that implementing prioritization, depending on firm characteristics and customer patience levels, can improve efficiency of omnichannel service systems. Li et al. (2013) examined the relationship between self-service checkout and the service environment, where multiple customers are impacted by the same service provision (e.g., inflight airline service). They found that the service quality received by a focal customer may impact the perceived service quality of other customers. Through a scenario-based experiment, they found that positive interactions between customers can improve service experiences and increase repurchase intentions. Ba and Johansson (2008) viewed a company's website as an e-service delivery system. Based on survey responses, they revealed that improvements in the e-service delivery system led to increased perceptions of ease of use, thereby enhancing customer satisfaction.

Emerging technologies, such as VTO, are reshaping the retail landscape by altering how customers engage with products and make purchasing decisions. This shift has profound implications, not only for industry practices but also for academic research (Islam et al. 2024). Research on VTO primarily explores its antecedents and consequences. For example, Kim and Forsythe (2008) and Zhang et al. (2019), utilizing online surveys, identified that perceived usefulness, entertainment value, and ease of use significantly enhance consumer attitudes towards VTO. Other studies have revealed notable benefits from VTO. Hwangbo et al. (2020), using qualitative data and interviews, found an increase in average sales per customer and a decrease in the return rate for retailers upon employing VTO. Similarly, Ghodhbani et al. (2022) found that VTO encourages consumer spending, while Kim (2016), through a field experiment, showed that VTO significantly reduces purchase risks and elevates shopping experiences. Merle et al. (2014) confirmed these findings in a lab experiment, illustrating that VTO positively influences consumers' willingness to purchase.

This research contributes to the literature by assessing the impact of VTO on sales performance across various retail formats. I assess the benefits of VTO to dual-channel retailers, which manage both offline and online storefronts, and compare these benefits to those accrued by pure online retailers. By evaluating the benefits of VTO to both dual-channel and pure online retailers, I assess the ability of the technology to complement offline operations, thus contributing to a successful multichannel retail strategy.

3.2. Retailer Channel Capabilities

The business value of customer-interfacing technologies, such as VTO, is closely tied to retailer channel capabilities, especially online channel capabilities. Channel capabilities denote an enabling characteristic of channels that better allow consumers to accomplish their shopping goals (Avery et al. 2012). Channels differ in their capabilities. For example, offline and online channels differ significantly in both the nature and extent of information they provide to consumers. Offline channels enable customers to physically interact with products such as clothing and eyewear, providing a tactile experience. In contrast, online channels excel at presenting detailed comparative information on various items, including prices, dimensions, colors, features, and functionalities.

In response to evolving consumer preferences, retailers have expanded their engagement strategies by employing multichannel sales channels, including offline stores, online platforms, catalogs, and mobile applications (Tang et al. 2021; Wang and Goldfarb 2017; Xu et al. 2017). A newly introduced channel may interact with existing channels, substituting for existing channels by replicating or surpassing their capabilities (Alba et al. 1997; Deleersnyder et al. 2002; Moriaty and Moran 1990), or by complementing existing channels, by introducing new characteristics that attract customers or stimulate additional purchases (Avery et al. 2012). For instance, an online channel may cannibalize a catalog channel due to its superior search capabilities and availability of product information. Conversely, online channels can augment offline channels by offering convenience and time-saving features not necessarily available to offline shoppers (Avery et al. 2012; Ren et al. 2022).

Researchers have explored the impact of new channels on sales performance through the lens of channel capabilities. For instance, Bang et al. (2013) investigated the effects of a new mobile channel on an existing online channel using 28-month panel data from a Korean e-marketplace. Their findings suggest that the influence of the mobile channel varies based on product characteristics, such as time criticality and information intensity. For products characterized by high time criticality and low information intensity, the mobile channel acts as a substitute for the online channel, whereas it complements the online channel for products with both high time criticality and high information intensity (Bang et al. 2013). In a study involving a U.S.-based specialty retailer, Wang and Goldfarb (2017) examined how physical store openings impact online channel performance, discovering that the effects (either substitutable or complementary) are contingent upon geographical locations, with store openings reducing online sales and search activities in regions where the retailer has a strong presence, while boosting them in less saturated markets.

Building on previous research, this study delves into scenarios where retailers enhance their online capabilities using customer-interfacing technologies, notably VTO. My research aims to advance the discussion on retailer channel capabilities by analyzing how the enhanced functionalities of online channels, following VTO implementation, impact sales performance for both pure online and dual-channel retailers.

3.3. Consumer Research Shopping

VTO, as a consumer-interfacing technology for search engagement, can enhance the capabilities of a retailer's online channels and may also complement the retailer's offline channels. Shopping for products includes both search processes and, subsequently, purchase processes (e.g., Bakos 1997; Ghose and Yao 2011). Both online and offline channels offer capabilities for searching and purchasing, thereby providing consumers with at least four distinct options for their research shopping: search offline and buy offline, search online and buy online, search online and buy offline, and search offline and buy online. Both the third and fourth options involve using both offline and online channels in the shopping process. The third option (search online and buy offline) is coined "webrooming", while the fourth option (search offline and buy online) is termed "showrooming" (Kumar et al. 2017). Among these four options, showrooming and webrooming have garnered significant attention from both researchers and practitioners.

Showrooming has been extensively investigated through both empirical and analytical studies. With showrooming, customers research options offline but purchase online, often to reduce purchase costs (Mehra et al. 2018). Using customer-level data from a U.S. fashion retailer to track purchasing behaviors, Kumar et al. (2019) found that retailers that opened offline locations, increased online purchases from existing customers, potentially indicating the showrooming effect. Similarly, Tang et al. (2021) found complementary impacts from online and offline channels in the retailing of shoes that may, in part, be attributed to showrooming. Bell et al. (2018) conducted a quasi-experiment using eyewear data and found that showrooming increases both online demand and total (online plus offline) sales. Moreover, showrooming behavior generated operational efficiencies, as customer service costs and product returns were reduced.

Analytical researchers have demonstrated that showrooming could result in diminished sales or reduced profits in either (or both) an online and offline channel (Balakrishnan et al. 2014; Gao and Su 2017; Zhang et al. 2020; Zhang et al. 2023). Balakrishnan et al. (2014), using a parsimonious model, found that reductions in offline prices inhibit the showrooming effect, reducing online sales, since customers will prefer to make their purchases offline. Gao and Su (2017) argued that the introduction of physical showrooms by online retailers may prompt retailers to reduce inventories, thus increasing stockout risk. Moreover, virtual showrooms, another example of AR technology, may increase online returns and hurt profits if excessive customers migrate from offline to online channels.

Through a theoretical model, Zhang et al. (2020) investigated “inter-product” showrooming, searching for one product offline but purchasing a different product online. They found that inter-product showrooming hurts retailers that have the same products in both online and offline channels. Zhang et al. (2023) investigated showrooming using a game theory model that included suppliers, retailers, and consumers. They found that showrooming can be a “win-win” strategy for suppliers and retailers when both the cost of customer physical store visits and a retailer’s marginal revenue from a customer visit are within an acceptable range.

A limited number of studies have used analytical models to examine webrooming. Jing (2018) modeled webrooming in a competitive situation, where product categories have limited match uncertainty (i.e., brands or features vary across channels), such as small appliances and consumer electronics. They found that if webrooming can fully resolve match uncertainty, retailers will have higher online sales. Jiao and Hu (2022) assumed offline and online channels provide distinct product information and found that consumers webroom, in part, for informational reasons. They also determined that consumers webroom to avoid waiting for product delivery.

Few empirical studies have examined the webrooming effect. Consumers engage in webrooming for both informational purposes, such as price comparisons (Flavián et al. 2016), and for noninformational reasons, such as to avoid shipping wait times (Jiao and Hu 2022). Moreover, webrooming can provide customers with a clearer idea of their purchase intentions by the time they enter a physical store (Fernández et al. 2018). Based on information processing and uncertainty reduction theories, Flavián et al. (2016) argued that consumers engage in webrooming to reduce purchase uncertainty and increase confidence in their purchase choice. They showed that the combination of online search and offline purchase, inherent in webrooming, enhances the search process and customer satisfaction with purchases.

In this study, I investigate the impact of VTO technology within the eyewear industry, analyzing its impact on both offline and online sales (Bell et al. 2018). I expect that VTO will significantly influence shopping behaviors across both online and offline sales channels. By enhancing online product presentations, VTO can increase sales revenues for online channels, but this increase may be at the expense of offline sales revenues. However, if the technology is complementary to the offline channel (e.g., by encouraging webrooming behavior), then offline sales should increase as well as online sales after this technology is implemented. Through this research, I aim to enhance the understanding of how innovative customer-interfacing technologies, such as VTO, can promote consumer research shopping and boost sales across both online and offline channels.

4. Hypotheses Development

4.1. Business Value of VTO Technology

In the online retail setting, VTO can improve channel capabilities in two ways. First, as a customer-interfacing technology, VTO may attract shoppers who would otherwise buy their products at physical stores. Researchers have demonstrated that the employment of customer-facing technologies can have a demand-expanding effect. For example, Oh et al. (2012), using survey data from 125 multichannel retailers in

Singapore, showed that integrating offerings across multiple channels through information technologies expanded a retailer's customer base. Ghose and Han (2014) found that demand increased when mobile technology was enhanced to allow users to complete transactions within an application. Adamopoulos et al. (2020) used empirical data from a multinational online retailer and found significant sales increases following the adoption of internet of things (IoT) technology.

A second way that VTO can improve online channel capabilities is by enriching the shopping experience. The technology provides customers with detailed product information, thereby reducing uncertainty and facilitating purchase decisions. VTO allows consumers to visualize product fit, a capability not available in the "standard" photo-based online shopping environment. In addition, VTO can make the online experience more enjoyable for the shopper (Reinartz et al. 2019). As a result, VTO can increase the conversion (shopping to purchase) rate for online consumers.

Combining the demand generating impact and the increased shopper conversion impact of VTO, I expect that the VTO technology will have a positive impact on a retailer's overall sales performance, as compared to retailers employing standard, photo-based shopping experiences. Thus, we propose the following hypothesis:

Hypothesis 1: *VTO technology positively impacts retailer sales.*

4.2. Pure Online Retailers vs. Dual-channel Retailers

VTO technology can significantly boost the capabilities of online retailers by providing detailed product visuals and extensive information, potentially enhancing online sales. Although VTO may not fully replace physical try-on facilities, it can improve on the information provided by a more static, photo-based online environment. VTO reduces uncertainties associated with product fit by enabling shoppers to virtually try on products, thus providing a previously unavailable simulation of fit in the online shopping environment.

For retailers operating both online and offline channels (dual-channel retailers), the impact of VTO technology is more ambiguous. While VTO may attract offline shoppers to a retailer's online channel, it may do so at the expense of the retailer's own offline sales channel. Conversely, since VTO cannot fully substitute for in-person try-ons, its use may complement the offline sales channel, allowing shoppers to virtually try on products before they head to physical outlets to finalize their purchases.

Thus, VTO may foster within-chain research shopping behavior where shoppers initially assess a product's fit online using VTO before visiting physical stores to verify the fit and complete their purchases (Aw 2020; Peck and Childers 2003). Enhancing online channel capabilities through VTO may help retain customers who prefer offline shopping, encouraging them to finalize transactions in-store. The offline environment provides certain advantages to shoppers, such as immediate product fit confirmation, elimination of shipping costs, and access to enhanced customer services (Aw 2020; Fang et al. 2021; Peck and Childers 2003; Reardon and McCorkle 2002).

In summary, while VTO technology can substantially enhance the capabilities of online channels, its impact on sales may differ between pure online retailers and dual-channel retailers. For pure online retailers, VTO can be instrumental in reducing uncertainties inherent in the lack of physical product interaction, thereby encouraging purchasing decisions, leading increases in overall sales. In contrast, for dual-channel retailers, the benefits from VTO are tempered by potential substitutability between offline and online channels. Thus, the benefits to dual-channel retailers depend on the strength of this substitution effect relative to potential complementarities between online and offline channels induced by VTO. Therefore, while the impact of VTO for pure online retailers should be unambiguously positive, its impact on dual-channel retailers may be either positive or negative. Thus, we hypothesize:

Hypothesis 2*:* *VTO technology has a greater positive impact on total sales for pure online retailers than for dual-channel retailers.*

5. Data and Research Design

5.1. Data

Data were collected and complied from multiple sources. Sales data were gathered from Earnest Analytics, a market research firm that compiles consumer spend data based on the purchase records of credit cards, debit cards, and store cards. The sample contains a panel of 6.5 million consumers across the U.S. who show consistent behavior in card spending, about 0.5% of households in each state. The sample is updated dynamically to capture active shoppers. If consumers stop using their cards, they are dropped from the sample.

Data from Earnest Analytics has been used in prior research (Kim and McCarthy 2024; Wang et al. 2023). It includes weekly online and offline sales for retailers. Both online and offline sales are reported at the retailer-city level based on consumer addresses (for online purchases) and store locations (for offline sales) where purchases were undertaken. City markets are defined by administrative boundaries as indicated by the U.S. Census, excluding surrounding suburban areas around a focal city.

There are 46 eyewear companies in the Earnest Analytics database. I exclude five companies that sell only contact lenses, nine companies that have only offline sales, and two companies that filed for bankruptcy and shut down operations during my study period. Finally, 30 companies remain in my dataset; 15 are pure online retailers and 15 are dual-channel retailers (i.e., with both online and offline stores). I selected U.S. city markets with populations greater than 250,000,[5] and collected weekly online sales generated by the consumers in these cities for retailers from January 2018 to December of 2021. The final dataset includes 30 eyeglass retailers selling to customers in 81 cities.

Information on the timing and use of VTO was gathered using the following approaches: I first determined whether a retailer had VTO on its website or mobile application. For retailers with VTO, I used four approaches to verify the implementation date of VTO technology. First, I searched press release announcements on retailer websites and public news articles on the Internet. If this step did not yield relevant information, I called retailer customer services representatives to inquire about start dates. If the companies did not share this information, I used an archive website (https://web.archive.org) to determine when VTO first appeared on a retailer's website. Finally, I searched retailer social media platforms, including Twitter (X) and Instagram, to find initial promotion posts for VTO. My searches revealed that 2 companies implemented VTO before January 2018 and 17 companies began using VTO during

[5] https://nces.ed.gov/programs/edge/docs/locale_classifications.pdf (Accessed in September 2023)

the study period, January 2018 to December 2021. The remaining 11 companies did not use VTO during my study period. Table in the Appendix A lists the eyewear companies in my dataset, along with VTO usage data.

Since my data spans the period 2018 to 2021, I control for the impact of COVID-19 pandemic government policy when estimating the business value of VTO. I collected information on containment and health policy from the Oxford Martin School.[6] To monitor policy responses to the COVID-19 pandemic, scholars at the Oxford Martin School compiled a containment and health index (CHI) composed of seven factors related to COVID-19 measures, including school closures, workplace closures, travel bans, testing polices, contact tracing, face coverings, and investments in vaccines (Hale et al. 2022). Index values vary from 0 to 100, with higher values indicating more severe COVID-19 containment and health policies in place (the value 0 indicates no containment and health policies in place).

5.2. Variables

The dependent variable is the dollar volume of a retailer's total sales in a city market. In particular, TTL_SALES_{rcwy} represents the total sales volume of retailer r in city c during week w in year y.

There are two independent variables. The first is VTO (VIR_TRYON_{rwy}), assessed with a dummy variable equal to 1 if retailer r offered VTO in week w of year y. Otherwise, this variable is equal to 0. The second independent variable measures the presence of offline stores for a retailer; that is, whether the retailer has dual channels in

[6] https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker (Accessed in September 2023)

a market ($DUAL\_CHANNEL_{rcwy}$). (Note, all retailers in our dataset have online channels.) If retailer r has an offline store presence in city c during week w of year y, $DUAL\_CHANNEL_{rcwy}$ is equal to 1. Otherwise, it is equal to 0.

I use the containment and health index (CHI_{cwy}) to gauge the intensity of COVID-19 pandemic restrictions within a market. As discussed above, CHI_{cwy} ranges from 0 to 100, where "0" implies that no extraordinary containment and health practices in place while "100" indicates the strictest policy. CHI serves as a control variable in my analysis of the business value of VTO, given that my data ranges from 2018 to 2021, encompassing the pandemic era.

Figure 2 graphs average weekly sales for eyewear retailers across all markets against CHI. As shown, sales volume follows a seasonal pattern. However, sales also appear to decrease when CHI increased at week 11 of 2020.

Sales vs. CHI

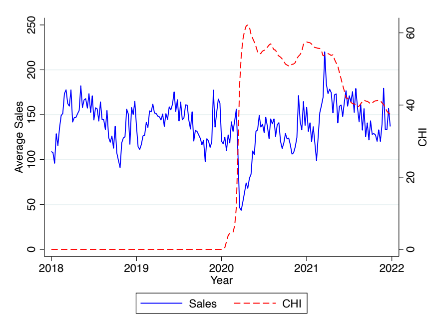


Figure 2. Average Weekly Total Sales and Containment and Health Measures

I include two control variables in my model. First, I add city-wide population (POP_{cy}), measured as population in city c in year y, to control for city demographic characteristics. This information is collected from the U.S. Census Bureau. Second, I add annual sales in the previous year in a city market ($ANN\_CITY\_SALES_{rc,y-1}$) to control for a retailer's market size in a specific city.

Table 1 and Table 2 present variable definitions and descriptive statistics, while Table 3 reports correlations among all variables. To check for potential multicollinearity, I compute variance inflation factor (VIF) scores for all independent and control variables. VIF scores range between 1.13 and 2.13, substantially lower than the commonly accepted cutoff of 10 (Kennedy 2003), indicating that multicollinearity is not a concern.

Table 1. Variable Definitions

	Variables	Definition
(1)	TTL_SALES_{rcwy}	Weekly total sales volume for a retailer in a week in a city market.
(2)	VIR_TRYON_{rwy}	Dummy variable indicates whether virtual try-on is adopted by a retailer in a week.
(3)	$DUAL\_CHANNEL_{rcwy}$	Dummy variable indicates whether a retailer has both offline and online sales channels.
(4)	CHI_{cwy}	Stringency index for the containment and health policy during the COVID-19 pandemic.
(5)	POP_{cy}	Population in a city market in a year.
(6)	$ANN\_CITY\_SALES_{rc,y-1}$	Total sales volume for a retailer in previous year in a city market.

Table 2. Summary Statistics

	Variables	Unit	# of obs.	Mean	Std. Dev.	Min	Max
(1)	TTL_SALES_{rcwy}[7]	Dollar	276,066	150.963	558.197	0	27028.17
(2)	VIR_TRYON_{rwy}	-	276,066	.308	.461	0	1
(3)	$DUAL\_CHANNEL_{rcwy}$	-	276,066	.404	.491	0	1
(4)	CHI_{cwy}	Index	276,066	24.743	25.890	0	77.763
(5)	POP_{cy}	Million Person	276,066	.829	1.187	.242	8.560
(6)	$ANN\_CITY\_SALES_{rc,y-1}$	Million Dollar	276,066	.008	.024	.001	.716

[7] The sales statistics from Earnest Analytics capture only 0.5% of household spending in each state. Total spending in a mean market can be estimated by multiplying the sales figures by 200.

Table 3. Correlation Table

	Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1)	TTL_SALES_{rcwy}	1.0000					
(2)	VIR_TRYON_{rwy}	-0.0877***	1.0000				
(3)	$DUAL\_CHANNEL_{rcwy}$	0.2175***	-0.2982***	1.0000			
(4)	CHI_{cwy}	-0.0080***	0.3005***	0.0086***	1.0000		
(5)	POP_{cy}	0.0493***	-0.0035+	0.0043*	0.0381***	1.0000	
(6)	$ANN\_CITY\_SALES_{rc,y-1}$	0.8168***	-0.1167***	0.2632***	-0.0054**	0.0587***	1.0000

Notes: + p<0.1, *p<0.05, ** p<0.01, *** p<0.001

5.3. Research Design and Model

My first goal is to estimate the business value of VTO on retailers' total sales (i.e., Hypothesis 1). My second goal is to compare the business value of VTO for pure online and dual-channel retailers (i.e. Hypothesis 2). VTO has been increasingly adopted by retailers in the eyewear industry. As noted above, two firms in my dataset implemented VTO before January 2018, the start of our data period, 17 firms started employing VTO during the collection period, and 11 firms did not offer VTO during the period of analysis. Figure 3 presents the cumulative number of retailers in my dataset employing VTO from 2018 to 2021.

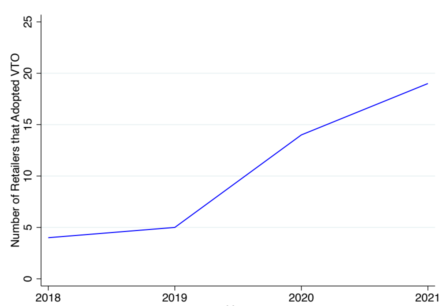


Figure 3. Total Number of Retailers That Adopted VTO by Year

To estimate the business value of VTO on sales, I construct the following econometric model. The dependent variable is $Ln(TTL\_SALES_{rcwy})$, and key the independent variables are VIR_TRYON_{rwy} and $DUAL\_CHANNEL_{rcwy}$. To compare the sales impact of VTO between dual-channel and pure online retailers, I add an interaction term, $VIR\_TRYON_{rwy} \cdot DUAL\_CHANNEL_{rcwy}$. I control for the severity of the pandemic through my variable, containment and health restrictions, CHI_{cwy}. As indicated above, I include POP_{cy} to control for city-level time varying effects and $ANN\_CITY\_SALES_{rc,y-1}$ to control for firm-level time varying effects. I also include retailer-city fixed effects and year and month fixed effects by including a vector of variables for $RETAILER\_CITY_{rc}$, $YEAR_y$, and $MONTH_m$ in my model. Finally, ϵ_{rcwy} is a random error term.

My model is specified as follow:

$$
\begin{aligned}
Ln(TTL\_SALES_{rcwy}) \quad &= \beta_0 + \beta_1 \cdot VIR\_TRYON_{rwy} + \beta_2 \cdot DUAL\_CHANNEL_{rcwy} \\
&+ \beta_3 \cdot VIR\_TRYON_{rwy} \cdot DUAL\_CHANNEL_{rcwy} \\
&+ \beta_4 \cdot CHI_{cwy} + \beta_5 \cdot POP_{cy} + \beta_6 \cdot ANN\_CITY\_SALES_{rc,y-1} \\
&+ \beta_7 \cdot RETAILER\_CITY_{rc} + \beta_8 \cdot YEAR_y + \beta_9 \cdot MONTH_m + \epsilon_{rcwy}
\end{aligned}
$$

5.4. Endogeneity

The decision to implement VTO technology is likely endogenous, as it may be influenced by various unobserved attributes specific to a retailer. To address the endogeneity issue, I implement an instrumental variable (IV) strategy, in line with the recommendations of prior literature (e.g., Miguel et al. 2004).

The cornerstone of this strategy is the selection of an IV that is strongly linked to the endogenous variable of interest, VIR_TRYON_{rwy} but is independent of the error term, ϵ_{rcwy}. I use the cumulative Google Search trend for "augmented reality" in the geographical location of a company's headquarters as my IV. The idea is that more

Google searches in the vicinity of a firm's headquarters for "augmented reality", the foundational technology for VTO, will be correlated with the firm's decision to implement VTO. Thus, the Google search trend data can be a proxy for regional technological advancements and consumer interest (Beugelsdijk and Jindra 2018; Lai and Guynes 1997). Moreover, these searches will not directly impact a firm's sales.

For the U.S.-based companies, this IV is derived from the cumulative search trend for "augmented reality" within the state where the firms are headquartered. For companies headquartered outside the U.S., the IV is based on the search trend data from their respective countries. For example, I use Georgia's search trend data for America's Best, a company headquartered in Atlanta, while Japan's search trend data is used for JINS, in line with the firm's Japanese origin.

6. Estimation Results: Business Value of VTO Technology

I use a two-stage least squares (2SLS) regression with the instrumental variables to estimate my model.[8] Table 4 shows the second-stage results of the 2SLS estimation. Table in the Appendix B shows the first-stage results. The Cragg-Donald Wald F statistics for the two models in the first stage estimations (5551.137 and 347.795) are statistically higher than the Stock-Yogo critical value (19.93), rejecting the null hypothesis that the instrumental variable is weak. The under-identification test using the Kleibergen–Paap rk LM statistic (e.g., Kleibergen and Paap 2006) is highly significant, rejecting the null hypothesis that the equation is under identified.

[8] I use the xtivreg2 command in Stata to estimate the 2SLS model. Following Wooldridge (2010), I also instrument all interaction terms that include VTO.

Hypothesis 1 argues that VTO technology positively impacts retailer sales. In Model 1.1 of Table 4, the coefficient for VIR_TRYON_{rwy} tests Hypothesis 1. The coefficient is positive and significant ($\beta = 0.331$; $p < 0.001$), indicating that VTO contributes to higher retailer sales by 33.1%. This result underscores the business value of VTO technology. Hence, Hypothesis 1 is supported.

Hypothesis 2 posits that VTO technology has a greater positive impact on total sales for pure online retailers than for dual-channel retailers. In Model 1.2 of Table 4, the coefficient for the interaction term between VIR_TRYON_{rwy} and $DUAL\_CHANNEL_{rcwy}$ is positive and significant ($\beta = 0.885$; $p < 0.001$), indicating that dual-channel retailers employing VTO technology experience greater increases in total sales compared to pure online retailers. This suggests that VTO is more beneficial for dual-channel retailers than pure online retailers. Therefore, Hypothesis 2 is not supported.

Table 4. 2nd Stage Estimation Results – Total Sales Performance

Ln (TTL_SALES_{rcwy})	Model 1.1	Model 1.2
VIR_TRYON_{rwy}	0.331*** (0.074)	1.151*** (0.197)
$DUAL\_CHANNEL_{rcwy}$	0.986** (0.327)	1.078** (0.339)
VIR_TRYON_{rwy}*$DUAL\_CHANNEL_{rcwy}$		0.885*** (0.197)
CHI_{cwy}	-0.002*** (0.000)	-0.003*** (0.000)
POP_{cy}	1.963*** (0.347)	1.785*** (0.355)
$ANN\_CITY\_SALES_{rc,y-1}$	7.308*** (0.596)	6.036*** (0.658)
Retailer City Fixed Effect	Included	Included
Year Fixed Effect	Included	Included
Month Fixed Effect	Included	Included
N	276,066	276,066
F Statistics	42.64***	40.38***

Notes: Robust standard errors in parentheses. + p<0.1, *p<0.05, ** p<0.01, *** p<0.001.

7. Extended Analysis: Encouragement of Consumer Webrooming

As anticipated, VTO technology improves channel capabilities, enhancing retail sales. However, surprisingly, VTO boosts sales for dual-channel retailers more than for pure online retailers. A plausible explanation for this result is that VTO encourages consumers webrooming, where consumers can virtually try on products but opt to purchase offline more.

To investigate this potential encouragement of VTO webrooming, I segment my analysis into offline and online sales. For offline sales, I assess the direct impact of VTO on dual-channel offline sales performance. For our online sales analysis, I consider both dual-channel and pure online retailers. Further, I utilize the closure of physical stores during the COVID-19 pandemic as a natural experiment to examine the potential for webrooming, as detailed below.

7.1. VTO Impact on Offline Sales: Encouragement of Direct Webrooming

For the offline sales model, I exclude pure online retailers to test the direct effect of VTO on offline sales. Therefore, the variable of $DUAL\_CHANNEL_{rcwy}$ is excluded from the model (since all observations are from dual-channel retailers). I use the same instrumental variable approach as in my base model, specified as follows:

$$\begin{aligned} Ln(OFF\_SALES_{rcwy}) \quad &= \beta_0 + \beta_1 \cdot VIR\_TRYON_{rwy} + \beta_2 \cdot CHI_{cwy} \\ &+ \beta_3 \cdot POP_{cy} + \beta_4 \cdot ANN\_CITY\_SALES_{rc,y-1} \\ &+ \beta_5 \cdot RETAILER\_CITY_{rc} + \beta_6 \cdot YEAR_y + \beta_7 \cdot MONTH_m + \epsilon_{rcwy} \end{aligned}$$

Model 2.1 in Table 5 reports my estimation result. The coefficient for VIR_TRYON_{rwy} is positive and significant, ($\beta = 0.369$; $p < 0.05$), indicating that VTO enhances dual-channel retailers' offline sales performance. This result suggests that offline sales increase after the adoption of VTO technology for dual-channel retailers. Thus, consumers appear to purchase at offline stores even though retailers offer virtually try-on options, suggesting that VTO encourages consumer webrooming.

Table 5. 2nd Stage Estimation Results – Offline Sales Performance

$Ln (OFF\_SALES_{rcwy})$	Model 2.1
VIR_TRYON_{rwy}	0.369* (0.176)
CHI_{cwy}	-0.014*** (0.001)
POP_{cy}	2.359*** (0.662)
$ANN\_CITY\_SALES_{rc,y-1}$	10.042*** (0.686)
Retailer City Fixed Effect	Included
Year Fixed Effect	Included
Month Fixed Effect	Included
N	86,880
F Statistics	143.90***

Notes: Robust standard errors in parentheses. + p<0.1, *p<0.05, ** p<0.01, *** p<0.001.

7.2. VTO Impact on Online Sales: Encouragement of "Reverse" Webrooming during Store Closure

I further use the unique circumstance of the COVID-19 non-essential store closures to estimate the potential impact of webrooming. The COVID-19 pandemic led to physical store closures. Thus, webrooming was suddenly rendered impossible and (previous) webrooming customers needed to buy their products online. Since webrooming is not possible for pure online retailers (that have no offline outlets), I estimate the online sales increase for the dual-channel retailers after physical stores are closed due to COVID-19 and compare this to the increase in sales experienced by the pure online retailers.

Information on non-essential store closure orders was collected from state government websites and from news sources, such as Wall Street Journal, New York Times, NBC News, USA Today, and Forbes. During closure orders, non-essential (physical) retail stores, including eyewear stores, were ordered closed (Wu et al. 2020). For example, the government of Alabama initiated an order requiring the closure of non-essential businesses on April 3, 2020, and lifted the order on April 30, 2020.[9] A dummy variable signifying that a non-essential business closure order is in effect in a market ($STORE\_CLOSE_{cwy}$) is used to replace CHI_{cwy}. This variable is equal to 1 if the order is in effect, and 0 otherwise.

To test the impact of VTO on the potential encouragement of "reverse" webrooming, I employ a triple interaction term encompassing VTO, dual-channel retailers, and store closures, after controlling for the main effects of these three variables and the dual interaction effects. The triple interaction term isolates the within-retailer VTO-enabled sales that migrated to the online channel during the lockdown period.

To capture the presence of this reverse webrooming effect, I limit the dataset to the pre-COVID-19 and initial COVID-19 period when store closures were in effect. In our dataset, I include 114 weeks during the pre-COVID-19 period and 14 weeks during the initial COVID-19 period to estimate online sales.

My main variables of interests include: VIR_TRYON_{rwy}, $DUAL\_CHANNEL_{rcwy}$, and $STORE\_CLOSE_{cwy}$. To construct the triple interaction model, I include the main effects and then add pair-wise interaction terms among these variables, as well as the triple interaction term, the standard setup for triple interaction models (Olden and Møen 2022). The triple interaction term (VIR_TRYON_{rwy} ·

[9] In addition, there were states, such as Arkansas, that required the closure of non-essential stores even though a stay-at-home order was not imposed. I include these closures in my database as well.

$DUAL\_CHANNEL_{rcwy} \cdot STORE\_CLOSE_{cwy}$) captures the reverse webrooming effect of VTO. Details of my analysis can be found in the Appendix C, and my model is specified as follows:

$$
\begin{aligned}
Ln(ONL\_SALES_{rcwy}) = {} & \beta_0 + \beta_1 \cdot VIR\_TRYON_{rwy} + \beta_2 \cdot DUAL\_CHANNEL_{rcwy} \\
& + \beta_3 \cdot STORE\_CLOSE_{cwy} \\
& + \beta_4 \cdot VIR\_TRYON_{rwy} \cdot DUAL\_CHANNEL_{rcwy} \\
& + \beta_5 \cdot VIR\_TRYON_{rwy} \cdot STORE\_CLOSE_{cwy} \\
& + \beta_6 \cdot DUAL\_CHANNEL_{rcwy} \cdot STORE\_CLOSE_{cwy} \\
& + \beta_7 \cdot VIR\_TRYON_{rwy} \cdot DUAL\_CHANNEL_{rcwy} \cdot STORE\_CLOSE_{cwy} \\
& + \beta_8 \cdot POP_{cy} + \beta_9 \cdot ANN\_CITY\_SALES_{rc,y-1} \\
& + \beta_{10} \cdot RETAILER\_CITY_{rc} + \beta_{11} \cdot YEAR_y + \beta_{12} \cdot MONTH_m + \epsilon_{rcwy}
\end{aligned}
$$

The results for the online sales model estimation are presented in Table 6. In Model 3.1, the coefficient for VIR_TRYON_{rwy} is positive and significant, ($\beta = 0.346$; $p < 0.05$), supporting the positive impact of VTO on retail online sales. In Model 3.2, the coefficient for $VIR\_TRYON_{rwy} \cdot DUAL\_CHANNEL_{rcwy}$ is negative and significant ($\beta = -1.085$; $p < 0.01$), suggesting that the impact of VTO on online sales is greater for pure online retailers compared to dual-channel retailers. Finally, in Model 3.5, the coefficient for the triple interaction term, $VIR\_TRYON_{rwy} \cdot DUAL\_CHANNEL_{rcwy} \cdot STORE\_CLOSE_{cwy}$, is positive and significant ($\beta = 3.839$; $p < 0.001$). This result suggests that the impact of VTO on dual-channel retailer online sales during the store closure period was higher than its impact on pure online retailer sales during the same period. Webrooming shoppers could no longer purchase products offline, therefore migrated online to make their purchases. The fact that more of these additional purchases were made at dual-channel retailers than at pure online retailers is a potential indication of this reverse webrooming effect.

Table 6. 2nd Stage Estimation Results – Online Sales Performance

Ln (ONL_SALES_{rcwy})	Model 3.1	Model 3.2	Model 3.3	Model 3.4	Model 3.5
	(Pre & During COVID-19 Non-Essential Store Closure)				
VIR_TRYON_{rwy}	0.346* (0.146)	1.232** (0.435)	0.211 (0.177)	0.334* (0.145)	4.792*** (1.419)
$DUAL\_CHANNEL_{rcwy}$	0.002 (0.093)	0.027 (0.094)	0.005 (0.093)	-0.014 (0.094)	0.100 (0.099)
$STORE\_CLOSE_{cwy}$	0.214*** (0.024)	0.195*** (0.026)	0.133* (0.052)	0.124*** (0.026)	0.867*** (0.256)
VIR_TRYON_{rwy}*$DUAL\_CHANNEL_{rcwy}$		-1.085** (0.398)			-4.562*** (1.269)
VIR_TRYON_{rwy}*$STORE\_CLOSE_{cwy}$			0.322 (0.202)		-3.098** (1.030)
$DUAL\_CHANNEL_{rcwy}$*$STORE\_CLOSE_{cwy}$				0.263*** (0.040)	-0.425* (0.210)
VIR_TRYON_{rwy}*$DUAL\_CHANNEL_{rcwy}$*$STORE\_CLOSE_{cwy}$					3.839*** (0.994)
POP_{cy}	0.518 (0.495)	0.588 (0.497)	0.512 (0.494)	0.513 (0.494)	0.788 (0.528)
$ANN\_CITY\_SALES_{rc,y-1}$	-0.726 (0.458)	-0.799+ (0.458)	-0.739 (0.458)	-0.786+ (0.458)	-0.907* (0.459)
Retailer City Fixed Effect	Included	Included	Included	Included	Included
Year Fixed Effect	Included	Included	Included	Included	Included
Month Fixed Effect	Included	Included	Included	Included	Included
N	173,978	173,978	173,978	173,978	173,978
F Statistics	26.10***	25.00***	24.75***	25.52***	21.81***

Notes: Robust standard errors in parentheses. + p<0.1, *p<0.05, ** p<0.01, *** p<0.001.

8. Concluding Remarks

8.1. Discussion of Findings

VTO is an innovative customer-interfacing retail technology that allows shoppers to virtually try on products online before making their purchases either online or offline. This technology reduces purchase uncertainty and enhances channel capabilities (Brady 2022), while improving retail sales performance. There are at least two reasons why VTO may contribute to higher sales. First, this innovative technology can attract new customers; that is, VTO can contribute to a demand-expanding effect (Brady 2022). Second, VTO provides customers with an enriched shopping experience, reducing uncertainty with product fit, and thus increasing the conversion rate from shopping to purchase. I find support for the positive impact of VTO on retail sales. Thus, my findings support the growing literature on the business value of customer-interfacing information technologies, such as VTO.

Surprisingly, my findings indicate that VTO technology contributes to higher sales gains for dual-channel retailers than for pure online retailers. This counterintuitive result may be attributed to complementarities between online and offline channels promoted by VTO. Specifically, the implementation of VTO may promote the webrooming effect, where shoppers search for products online but finalize their purchases offline.

There are several reasons why VTO may promote offline purchases. Although it aids in reducing the uncertainties associated with online purchases, it cannot completely replace the positive benefits from offline shopping. For example, for eyewear consumers, purchasing through physical stores can alleviate shipping costs and delays, and potentially offer lower total purchase costs after considering shipping fees (Reardon and McCorkle 2002). Additionally, physical store representatives can provide essential pre-purchase and post-purchase services, such as conducting eye examinations and facilitating health insurance claims. Customers also benefit from the ability to use coupons and make payments via preferred methods, such as cash, when shopping in physical locations (Fang et al. 2021).

Overall, I find that VTO helps dual-channel retailers gain greater sales than pure online retailers. To gain deeper insights into my results, I investigate VTO's impact on both offline and online sales. First, for dual-channel retailers, I find that VTO significantly improves offline sales, consistent with webrooming behavior. Second, I leverage the closure of physical retail outlets during the COVID-19 period to examine online purchases for both dual-channel and pure online retailers. With physical stores closed, an increase in online sales is to be anticipated for both retailer types. My analysis, however, shows that dual-channel retailers equipped with VTO technology achieved higher online sales gains than pure online retailers with VTO. Moreover, their sales gains exceed the performance of dual-channel retailers without VTO. These observations suggest a "reverse" webrooming effect, whereby VTO improved online purchasing during the period of physical store closures, underscoring its role in boosting digital customer engagement and retention.

Overall, my findings support the business value of VTO for both pure online and dual-channel retailers. Consumers can use VTO to search online and make their purchases either online or offline. Webroomers may be encouraged to use VTO to narrow their purchase options online and then purchase offline to seek lower prices, redeem coupons, complete medical insurance forms, make cash payments, physically try on products, consult with sales associates, reduce the wait time for product possession, and receive assistance with product fitting. Thus, I achieve the surprising result that dual-channel retailers obtain greater benefits from VTO than do pure online retailers.

8.2. Theoretical contributions

This study makes several contributions to the literature. First, I contribute to the literature on customer-interfacing retail technologies (Grewal et al. 2020; Roggeveen and Sethuraman 2020; Sethuraman and Parasuraman 2005). Technologies, such as VTO, represent a significant evolution in how retailers engage with consumers, offering enhanced service experiences and operational efficiencies. Previous research has emphasized convenience and social presence as key factors driving the adoption of these technologies (Grewal et al. 2020). Additionally, the ability of these technologies to facilitate various stages of the shopping process, from demand generation to post-purchase services, highlight their transformative potential in retail settings (Roggeveen and Sethuraman 2020). My study extends this understanding by analyzing the impact of VTO on sales performance. In addition, while prior analytical work, such as Beck and Crié (2018), Kim and Forsythe (2008), and Merle et al. (2014), focused on VTO from a consumer perspective, my research assesses its business value from a retailer's perspective. Importantly, by comparing sales performances between dual-channel and pure online retailers, I show that VTO complements, rather than substitutes, for a retailer's physical channel.

Secondly, my study enhances the body of knowledge on channel capabilities (Avery et al. 2012). Channel capabilities have been examined in terms of the implications of the introduction of new channels, as evidenced by Bang et al. (2013) and Wang and Goldfarb (2017). The integration of customer-interfacing technologies within these capabilities is critical for facilitating transitions between online and offline channels, thus enhancing consumer engagement (Avery et al. 2012). Furthermore, existing studies have shown that new channels may interact with existing channels, either as substitutes or complements (Alba et al. 1997; Deleersnyder et al. 2002; Moriaty and Moran 1990). Building upon these foundational studies, this research focuses how VTO technology influences both online and offline sales performance. My finding highlights that dual-channel retailers experience greater sales increases than pure online retailers after implementation of VTO, a result that supports a multichannel retailing strategy.

Lastly, my research delves into consumer research shopping by exploring the impact of VTO technology on the encouragement of consumer webrooming. The phenomenon of webrooming has gained traction as a critical aspect of multichannel retailing. Empirical studies suggest that webrooming enhances the search process, reduces purchase uncertainty, and increases customer satisfaction (Flavián et al. 2016; Jiao and Hu 2022). This study focuses on the application of VTO technology within the eyewear industry, revealing how VTO significantly influences purchasing behavior across both online and offline channels. My findings underscore the potential of VTO to drive sales by synergizing online and offline shopping experiences. Thus, I contribute to a broader understanding of how innovative customer-interfacing technologies, such as VTO, can transform consumer research shopping and boost overall sales performance.

8.3. Managerial Implications

First, my study illuminates the business value of VTO, by demonstrating its positive impact on retail sales. As a critical customer-interfacing tool, VTO offers substantial benefits by enabling customers to “try on” products within a virtual environment. This innovative feature can enhance customer confidence in purchase decisions, thereby increasing the likelihood of completing transactions and improving overall sales performance (Szeja 2023). With advancements in VTO technology, it may be increasingly advisable for a broader spectrum of retailers, including both pure online and multi-channel retailers, to adopt this technology (Brady 2022).

Secondly, my findings indicate that dual-channel retailers can enhance sales in their physical outlets by deploying VTO technology. This increase in sales is likely facilitated by VTO's ability to promote webrooming, where customers research products online before making offline purchases. In contrast to pure online retailers, dual-channel retailers are better positioned to capture and retain sales from webroomers within their own network, discouraging customers from switching to competitors. Therefore, integrating VTO into a comprehensive multi-channel strategy is beneficial for maintaining and boosting sales.

Finally, my findings reveal that dual-channel retailers equipped with VTO technology secure a notable competitive advantage during unexpected offline store closures (Bhattarai 2020). The COVID-19 pandemic highlighted the inherent unpredictability of business environments and the critical need for resilient operations (Cohen and Kouvelis 2021; Craighead et al. 2020; Dohmen et al. 2023; Pournader et al. 2020). Dual-channel retailers that integrate VTO services can offer both physical and virtual try-on options across channels, giving them a competitive advantage during market disruptions. In the face of ongoing market uncertainties, it is strategically prudent for retailers to invest in technological "insurance" that can maintain business continuity and mitigate risks from future adversities (London 2021).

8.4. Limitations and Future Research

This paper is not without limitations. First, I only use the eyewear industry for my empirical research sample. Future research can study the impact of this technology on other retail sectors, such as cosmetics, apparel, and shoes. Second, I use sales volume as my measurement of performance. I do not consider the impact of VTO or webrooming on other performance measurements, such as profitability. One potential extension of this paper would be to analyze the impact of VTO on a more comprehensive array of performance measures. Finally, I observe changes in sales due to the implementation of VTO at an aggregate level. Future researchers may gain greater insights into tracking actual consumer behavior following the implementation of technologies, such as VTO, with methods including field experiments, lab experiments, or revealed preference models.

Chapter 2: Scanning While Shopping: Assessing the Impact of Mobile Consumer Scanning Technology on Retail Performance

1. Introduction

The retail industry has experienced significant changes over the past two decades, often influenced by digital advancements. Technologies employed by retailers have contributed to shifts in operations and have reshaped shopping expectations and behaviors. The most important technology advancement has been the advent of online retailing (Peinkofer et al. 2015). However, as online retailers have expanded their reach, physical retailers, too, have used technologies to better compete with their online rivals. A notable development in this context has been the introduction of mobile consumer scanning technology (MCST), a system that enables consumers to scan products with mobile devices while shopping. MCST expedites the checkout process and allows customers to better track their purchases, thus, enhancing the shopping experience (Shi et al. 2021).

Retailers that employ MCST transfer logistics processes traditionally undertaken by the retail employees to consumers. Thus, MCST can be considered a consumer logistics (CL) application. CL encompasses the planning, execution, and management of activities that consumers engage in to acquire, store, and utilize products during their shopping journey (Granzin and Bahn 1989; Hüseyinoğlu et al. 2020). Since the MCST application requires consumers to scan products while they shop, these scanning operations are shifted by the retailers to consumers with the intent to create more efficiencies in logistics operations and to enhance the customer experience (Monnot et al. 2022; Ta et al. 2015).[10]

[10] Even with self-scanning checkouts, retailers need to monitor the self-checkout lanes.

MCST has been adopted by industry frontrunners, including the largest retailer in the U.S., Walmart (Pinhammer 2021). Highlighting the adoption of this technology, RBR, a prominent consultancy, predicts a significant surge in the worldwide uptake of MCST, projected to reach 160,000 stores globally by 2027, up from 46,000 in 2021 and 36,600 in 2020 (Walk-Morris 2022).

Given the growing prominence of MCST in the retail sector, this study investigates the costs and benefits from the implementation of the technology using a case study from a prominent U.S.-based retailer. The aims of the study are to determine whether this consumer-centered technology has achieved the benefits highlighted by the retailer and to explore potential unintended consequences from MCST.

Meijer, a leading general merchandise and grocery retail chain in the Midwest of the United States launched its MCST technology, called Shop & Scan, in November 2017, focusing initially on its Michigan stores. Beginning as a pilot in seven stores, the program subsequently expanded to encompass over 100 stores within the state, as well as locations in other states. The technology permits shoppers to use their mobile phones to scan product barcodes as products are taken off the shelf and put into shopping baskets. Shoppers account for chosen items in a digital cart and finalize purchases via the Meijer mobile application and self-checkout screen (see Figure 1).

(1a) Interface

(1b) Shop & Scan Checkout Lane

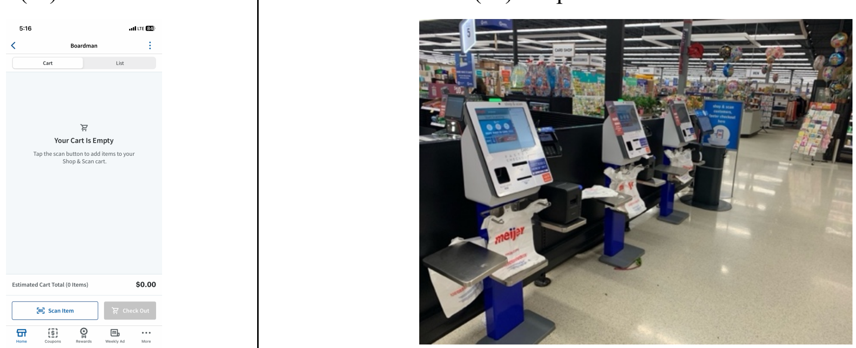


Figure 1. Shop & Scan and Checkout Lane

According to both my interviews with Meijer managers[11] and my reading of secondary sources,[12] the primary purpose for the adoption of MCST was to enhance the customer experience by expediting the checkout process (see Figure 2). Delays at checkout counters have been exacerbated by difficulties in hiring sufficient service representatives to meet labor demands at checkout. Since MCST allows shoppers to bypass regular checkout lines, including self-scanning checkout lines (since items have already been scanned), the decision to adopt this technology was seen by Meijer as a key to improving the customer experience and alleviating a labor shortage.

Figure 2. Meijer's Shopping Cart

According to Meijer's Chief Information Officer, within five months of initiation of the technology in the first seven stores, the MCST mobile application was downloaded by more than 12,000 customers.[13] Once downloaded, the technology was used by over 80% of Meijer customers in possession of the mobile application. My own discussions with a store-level customer service

[11] My interviews with a Meijer's customer service manager on March 21, 2023, and with assistant store manager on September 16, 2024.
[12] https://www.meijer.com/services/shop-and-scan.html (Accessed in October 2024)
[13] https://newsroom.meijer.com/2018-04-16-Meijer-Announces-Innovative-New-Technology-To-Improve-Customer-Experience (Accessed in May 2024)

manager (see Footnote 11) indicated that 35-40% of customers at that location actively used Shop & Scan, demonstrating significant consumer engagement with the technology.

A popular feature of Meijer's MCST mobile application, according to the firm's Director of Customer Experience, is the ability for customers to create digital shopping lists and run ongoing pre-tax expense totals while shopping.[14] Thus, this technology not only expedites the checkout process, but also increases the ability of consumers to monitor their pre-tax spending while they shop. Given this key feature of the MCST technology, an unintended consequence of its use may be a reduction in shopper transaction or basket size. As noted by researchers in the behavioral economics and marketing areas, when shoppers can track their spending in real time, they may reduce their purchases due to price transparency and mental accounting (Prelec and Loewenstein 1998; Thaler 1985).

Despite a wealth of research on consumer logistics (e.g., Carbone et al. 2017; Ta et al. 2015; Wang et al. 2022) and on mobile applications (e.g., Deng et al. 2022; Ghose and Han 2014; Lee et al. 2020; Son et al. 2020; Sun et al. 2019), studies that focus on MCST remain limited. Shi et al. (2021) showed that MCST provides both operational and strategic benefits to retailers through the provision of information on shopping behaviors. Ferreira et al. (2023) identified that the continued use of mobile self-scanning applications by retailers hinges largely on user satisfaction and perceived usefulness, with factors such as technology readiness and perceived quality of the application contributing to its successful implementation. I contribute to this literature by examining the costs and benefits from the implementation of MCST. In particular, I ask the following questions: (1) Does MCST reduce in-store dwell time, as suggested by Meijer managers? (2) Does MCST result in increased customer visits, as would be expected by a

[14] https://newsroom.meijer.com/2019-09-17-Meijer-Expands-Shop-Scan-Technology-to-All-Stores (Accessed in May 2024)

technology that enhances the customer experience (Ishfaq et al. 2022)? (3) Does MCST have the unintended consequence of reducing the average transaction size of shoppers, as suggested by the literature on pricing transparency and mental accounting? (4) Finally, to enhance the understanding of the impact of MCST on retailing, I ask how the technology may contribute to changes in consumer shopping patterns and retailer's sales volume.

To address my research questions, I use datasets from two sources: Meijer store traffic data, including monthly average in-store dwell time and total store visits, are collected from Placer.ai, while information on Meijer's customer transactions is collected from Earnest Analytics. Using a weighted stacked difference-in-difference (DID) model, I find that the implementation of MCST by Meijer has led to a decrease in customer in-store dwell time, as predicted by Meijer management. Moreover, the technology contributed to an increase in total store visits, as might be expected from a technology that enhances the customer experience. Furthermore, I find that the technology contributed to a decrease in average transaction size per shopping visit, as predicted by the theoretical papers on price transparency and mental accounting.

In my extended analysis, I show that MCST boosted both the number of unique customers and the average number of visits per customer. Therefore, the technology promoted both a higher customer base and increased visits by current customers. Additionally, although reducing consumer's transaction size, MCST increases store visits, ultimately leading to an increase in retailer sales volume. Moreover, customer shopping patterns changed after the implementation of MCST with its impact varying by day of the week.

This research makes several key theoretical contributions. First, this paper advances the CL literature (e.g., Carbone et al. 2017; Ta et al. 2015; Wang et al. 2022) by focusing on how a consumer-centered retail technology can alter shopping patterns and retail performance. Second, I contribute to the literature on mobile applications. While the adoption, use, and performance of mobile applications has been thoroughly explored (e.g., Deng et al. 2022; Ghose and Han 2014; Lee et al. 2020; Son et al. 2020; Sun et al. 2019), studies addressing MCST are limited. Shi et al. (2021) and Ferreira et al. (2023) focused primarily on the information value and consumer acceptance of MCST. Building on these insights, this study examines the impact of MCST on retailer performance metrics, thus contributing new perspectives to the relationship between mobile technology and retailer outcomes. Third, I advance the understanding of how price transparency and mental accounting impact purchasing transactions. MCST provides real-time visibility of total spending, promoting greater price transparency and encouraging consumers to adhere to their budgets. Prior studies have examined how various factors influence consumer spending, including return policies (Wang et al. 2024), consumer emotions (Nichols et al. 2015), product assortment (Mani et al. 2022; Martin et al. 2020), and sales promotions (Ramanathan and Dhar 2010). My research extends this body of work by showing how MCST influences transaction size, offering insights into how price transparency reshapes consumer spending behavior and purchasing patterns.

This research also provides critical managerial insights. First, the real time tracking of shopper purchases through MCST opens the way to retailer promotions that target consumers as they shop. These targeted promotions may offset the reduction in spend per shopping visit attributed to the technology. Second, my finding that MCST changes customer shopping patterns may lead retailers to alter their staffing requirements to increase efficiency and enhance the customer experience. Moreover, MCST provides valuable consumer data on basket composition and purchasing patterns that can enhance decision-making in areas such as demand forecasting, inventory management, and marketing.

2. Literature Review

Retailers have increasingly utilized a range of mobile technologies to enhance the customer service experience. This study examines the influence of Shop & Scan technology, a form of MCST, on retailer outcomes, including customer demand and shopper transaction size. To place my paper in the context of the literature, I review studies in four distinct areas: the first focusing on consumer logistics, the second delving into retailing mobile applications, the third into self-scanning technology and MCST, and the fourth concentrating on price transparency and mental accounting.

2.1. Consumer Logistics (CL)

Consumer Logistics (CL) refers to the array of logistical activities that consumers perform to facilitate the movement, storage, and disposal of goods and services within the consumption process (Boyd and McConocha 1996; Hüseyinoğlu et al. 2020). Granzin and Bahn (1989) developed a comprehensive framework for consumer logistics, positing that households often operate their own distinct, autonomous logistics systems. They identified five core subsystems in consumer logistics: location, inventory, transportation, handling and storage, and communication.

Building on this foundation, research on consumer logistics has highlighted consumers as value co-creators in various service contexts. In the business-to-consumer setting, Ta et al. (2015) redefined traditional roles by illustrating how consumers actively participate in product development, order management, and customer service. Similarly, in omnichannel retailing, Wang et al. (2022) identified key consumer activities, such as selecting product options, tracking orders, and utilizing pickup services, which are traditionally handled by logistics providers. In consumer-to-consumer environments, Carbone et al. (2017) demonstrated how digital platforms enable consumers to offer logistics services, such as local delivery and storage, transforming consumers into logistics service providers. Monnot et al. (2022) further integrated these perspectives by categorizing consumer logistics into domains, such as transportation, storage, logistical planning, and outbound logistics, providing a comprehensive view of consumer-driven logistics activities.

Within the context of consumer logistics, MCST enables shoppers to engage in a variety of logistical tasks through their mobile devices including the following:

- Real-Time Product Scanning: Consumers use their mobile devices to scan products as they are pulled off store shelves and placed into shopping carts (Shi et al. 2021). The MCST application provides shoppers with access to detailed product information, including prices, so that shoppers can monitor their spending totals in real time (Bahn et al. 2015).
- Inventory Management: Consumers can manage their personal inventories by tracking purchases, monitoring stock levels, and setting alerts for low-stock items (Boyd and McConocha 1996; Inman and Nikolova 2017).
- Order Customization and Checkout: MCST enables consumers to modify product selections, apply discounts, and complete payment transactions (Hüseyinoğlu et al. 2020). The application allows shoppers to bypass traditional checkout lines, thus enhancing the overall shopping experience (Ferreira et al. 2023).

Given the promises of MCST to improve the shopping experience, I investigate the impact of the technology on in-store dwell time, monthly store visits, and average transaction size. Moreover, I determine how MCST changes shopping patterns and retailer's sales volume.

2.2. Retailing Mobile Applications

Mobile applications can have strong positive impacts on consumer engagement (Viswanathan et al. 2017), and have sparked extensive research across various industry contexts, such as gaming (Kwon et al. 2016), advertising (Adikari and Dutta 2021), and the news industry (Xu et al. 2014). I focus my literature review on the retail sector, particularly on the adoption, use and performance of mobile applications in this sector.

Numerous studies have explored factors that influence the adoption of mobile applications by consumers. Sun et al. (2019), for instance, conducted a randomized field experiment to examine the drivers of mobile application adoption. They discovered that in the short run, both monetary incentives and the provision of product information could increase mobile application adoption. However, in the longer term, only the provision of product information had a positive impact on customer purchases and provider profits. These findings underscore the importance of the provision of practical and relevant information on retail mobile applications.

The features and performance of mobile applications have also been the subject of numerous studies. Ghose and Han (2014) examined the role of in-application purchase options and in-application advertisements on application demand. They found that the availability of in-application purchases boosted demand, while in-application advertisements reduced demand. In a related vein, Deng et al. (2022) analyzed the impact of the "freemium" strategy, where basic services are provided for free, but charges apply for more advanced application features. They found that the presence of a free version of an application led to an increased demand for the paid version of the same application.

Son et al. (2020) delved into customer adoption of retail loyalty applications, such as applications that provide sales promotions to loyalty program members. They found that loyalty application adoptions were associated with increases in retail purchases. However, customers that adopted these applications also showed a tendency to favor highly discounted, low-margin products. Moreover, loyalty program customers tended to visit more retailers while spending less at each of the retailers, thus, surprisingly, demonstrating lower loyalty to specific stores. Along this line, Lee et al. (2020) studied mobile application recommendation systems (i.e., applications that recommend specific products based on purchasing behaviors and retailer priorities) and how they influenced online consumer shopping decisions. They found that the recommendation systems increased customer website and mobile application views, click-through rates, basket-to-sales conversion rates and sales of recommended products,

This study focuses on the MCST application implemented by the grocery and supermarket store chain, Meijer. This application allows customers to scan product barcodes, accumulate items in digital carts, and finalize purchases via a self-checkout screen without further product scanning. I expect the MCST program to reduce in-store dwell time, increase customer store visits, and reduce average transaction size.

2.3. Self-Scanning Technology and MCST

The deployment of self-service technologies has dramatically changed how retail services are conceived, developed, and delivered (Meuter et al. 2005; Looney et al. 2008). Various forms of these technologies have been implemented, including self-checkout stations and MCST, each offering distinct operational advantages.

Self-checkout technology represents an automated system allowing consumers to independently scan, bag, and pay for their purchases that reduces the need for cashier interaction (Inman and Nikolova 2017). Self-checkout has been widely adopted by retailers, such as Costco, Walmart, and Target (Opara-Nadi 2005). Based on a global survey of 2,803 consumers conducted by NCR, 90% of respondents reported that they used self-checkout lines for convenience, speed, and simplified check-out (NCR 2014). Thus, the technology can allow consumers to expedite their check-out process, and retailers to reduce cashier labor costs (Grewal et al. 2017). On the negative side, consumers may often experience problems scanning products, delaying their checkout process, while retailers can realize increased theft rates after employing the technology, as some shopper may “forget” to scan items (Thakker 2019).

In recent years, a new mobile-based self-scanning technology, MCST, has been adopted by retailers. MCST is distinct from self-checkout in three ways. First, MCST allows customers to use their smartphones or a retailer’s mobile equipment to scan items as they place them into shopping carts, while with self-checkout, items are scanned at the end of the shopping trip (Inman and Nikolova 2017). Second, with MCST, information on scanned items is stored in the mobile application allowing customers to monitor their spending as they shop. Third, MCST provides digital records of purchases, facilitating the creation of digital shopping lists as customers shop in physical retail outlets. MCST allows retailers to integrate their online channels with their offline channels, enhancing the customer experience and improving retailer performance.

Despite the increasing adoption of MCST, academic research on this technology remains limited, with a few notable exceptions. Shi et al. (2021) examined MCST as a type of interorganizational information technology. Their theoretical model demonstrated that MCST has dual uses: operationally, it allows suppliers to accurately deduce demand from scan data, resulting in substantial inventory cost reductions; strategically, MCST can enhance the value of information sharing within supply chains.

Ferreira et al. (2023) explored the factors impacting the use of MCST in retail settings. Based on survey data from a large supermarket chain in Portugal, they revealed that MCST usage is influenced by user satisfaction and perceived usefulness. The study found that greater propensity to adopt and use technologies (i.e., greater technology readiness) (Parasuraman 2000) significantly improved MCST perceived usefulness, positively impacting user satisfaction.

In contrast to previous studies, my research examines the impact of MCST on customer behavior and retailer performance. This technology enables customers to scan product barcodes, accumulate items in a digital cart, and complete purchases at a self-checkout screen without additional scanning. I examine the impact of this technology on customer in-store dwell time, customer store visits, and shopper transaction size.

2.4. Price Transparency and Mental Accounting

Price transparency refers to visibility and accessibility of information on the price of goods and services (Rossi and Chintagunta 2016). In the retailing industry, price transparency has been enhanced through technology applications, notably through search engines and product comparison tools (Hanna et al. 2019). For example, KAYAK, a metasearch engine for travel services, helps consumers track flight prices before they purchase airline tickets. Moreover, KAYAK's price forecasting tool tracks price tendencies, providing suggestions to consumers as to the best time to purchase tickets.[15]

[15] https://www.kayak.com/news/kayak-confident-traveler/ (Accessed in June 2024)

Mental accounting is a framework within psychology and behavioral economics that describes how consumers categorize, evaluate, and manage their financial activities. Mental accounting theory states that consumers divide their spending budget into different mental accounts based on various criteria, such as the source of money, intended use, or the nature of expenditures (Thaler 1985). For example, consumers may implicitly set budget limits for various categories of products before shopping at a grocery store. Consumers use these mental accounts to monitor their spending, especially as spending approaches various budget ceilings.

Mental accounting affects the way that consumers spend by setting upper limits on expenditures by product category (Prelec and Loewenstein 1998). Moreover, price transparency may facilitate mental accounting, notably the ability to monitor spending in real time, as with running totals at gasoline pumps or on taxi meters. For example, as the total at the gas pump approaches a subjective limit (e.g., $50), a consumer may choose to limit their purchase rather than fill the tank.

Applications that facilitate price transparency and mental accounting may motivate self-control over spending behavior (Shefrin and Thaler 2004). Mental accounting can serve as a self-control mechanism, connecting income and expenses to specific activities while constraining total budgets (Heath and Soll 1996). Moreover, tracking costs through mental accounts helps ensure that consumers do not exceed their budget limits (Cheema and Soman 2006; Gourville and Soman 1998; Thaler 1985).

Given changing customer behavior with price transparency, increases in transparency may influence retail decisions. If prices are transparent, retailers may monitor prices charged by rivals and adjust their own prices, accordingly. For example, Rossi and Chintagunta (2016) found that average gasoline prices on Italian highways decreased by 1 euro cent per liter when prices were posted at fueling stations. Similarly, Grennan and Swanson (2020) found that when a hospital had access to purchase prices paid by peer hospitals, they were able to negotiate significant discounts with suppliers.

This research develops the understanding of price transparency and mental accounting from the perspective of technology adoption. In my research, MCST transforms the shopping experience by offering real-time price transparency, allowing consumers to monitor their running totals as they shop, thus impacting shopping expenditures.

3. Hypotheses Development

I develop my hypotheses based on characteristics of MCST, consumer logistics, price transparency, and mental accounting. Specifically, I focus on the relationship between MCST and two store traffic performance measures, in-store dwell time and store visits, and one sales performance measure, consumer transaction size.

MCST is designed to streamline the checkout process in retail stores by allowing customers to scan items directly into their shopping carts as they shop. This technology enables customers to bypass traditional checkout lines, effectively reducing in-store dwell time. Furthermore, MCST facilitates concurrent product bagging throughout the shopping journey, which enhances the overall efficiency of the shopping experience. In addition to benefiting MCST users, the technology also may impact non-MCST users. If MCST customers use dedicated checkout lanes, traditional checkout lanes, both self-service and cashier-operated, may experience reduced congestion. This redistribution of customers can result in shorter wait times for all types of store shoppers, including those using standard checkout methods. Accordingly, I hypothesize:

Hypothesis 1: *Mobile consumer scanning technology decreases customers' average in-store dwell time.*

MCST enhances the customer experience by shortening the time to check out after shopping. Moreover, it may free checkout lanes for non-MCST, thus improving their customer experience as well. Furthermore, MCST offers pricing transparency while customers shop which may resonate with consumers who value clear financial management and budgeting. The technology provides customers with continuous visibility of their running totals that can help maintain shopping budgets. Improved customer experiences resulting from the implementation of MCST through its price transparency and improved check-out procedures may increase shopping frequency and attract new customers. Thus, I posit:

Hypothesis 2: *Mobile consumer scanning technology increases total store visits.*

Enhanced price transparency through MCST usage enables consumers to monitor their spending while they shop, allowing for more informed purchase decisions. Grounded in mental accounting, MCST facilitates real-time tracking of expenditures, which helps consumers adhere to their financial budgets. Consumers allocate specific budgets for spending categories and regulate their expenditures within these limits (Heath and Soll 1996; Prelec and Loewenstein 1998; Thaler 1985). By providing a live update of their pre-tax spending as items are added to the digital cart, MCST enhances consumers' financial awareness and control. Given the capabilities of MCST to provide real-time financial monitoring, I propose the following hypothesis:

Hypothesis 3: *Mobile consumer scanning technology decreases average spend per shopping visit.*

4. Research Design

4.1. Research Context

Meijer first implemented Shop & Scan technology in 2017. To access the Shop & Scan program, customers download the Meijer mobile app and choose their store location. While shopping, customers scan product barcodes, through which product data, such as product name and unit price, are transferred to a digital cart (Figure 3a). At checkout, customers scan a QR code on the self-checkout screen to transfer products from the digital cart into the store's payment system and then pay for their purchases without having to rescan their purchases (Figure 3b).

(3a) Product Scan (3b) Payment Process

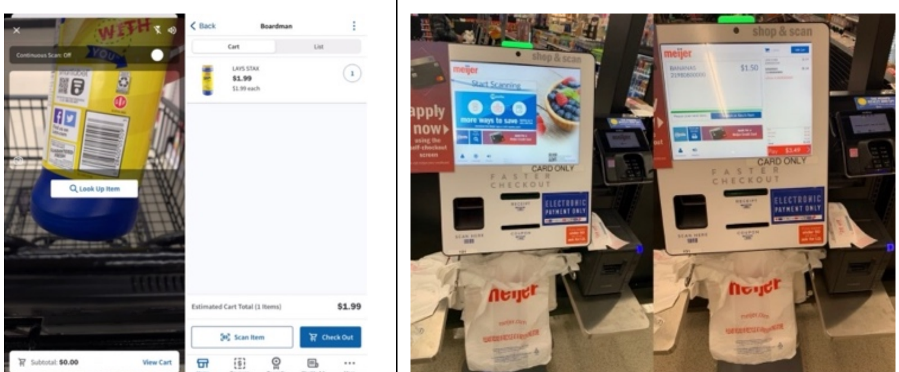


Figure 3. Shop & Scan Purchasing Procedures

Meijer implemented Shop & Scan technology in waves at its physical stores. I focus on the implementation of the technology in Michigan, where it was first introduced by the retailer.[16] In the first wave in November 2017, seven stores located in five cities adopted the Shop & Scan technology. In June 2018, 39 additional stores implemented Shop & Scan in the second wave. These 39 stores included locations in the Grand Rapids metropolitan area, along with stores in

[16] Although Shop & Scan has expanded to all Meijer stores in six states in the U.S., I focus on stores exclusively in Michigan due to data availability.

western Michigan. The third implementation wave included 27 stores, mainly in Flint, Jackson, Saginaw, Traverse City, and their suburbs. Unlike the first two waves, where the technology was implemented simultaneously in all stores, the third wave was implemented at the different locations over a 14-month period (July 2018 – August 2019). Since exact implementation dates for these 27 stores cannot be determined, they are excluded from my dataset. The last wave (the third wave included in my dataset) contains the 42 stores in southeastern Michigan that adopted Shop & Scan after the end of my data collection period and thus are not examined as part of a treatment group but are used in our control group.[17]

4.2. Research Methodology – Difference-In-Difference Estimation

I examine the impact of Shop & Scan on my performance variables using a quasi-experiment. Specifically, I employ the difference-in-difference (DID) estimation technique to assess the effects of Shop & Scan. Similar methods have been used by many researchers, such as Balthrop et al. (2024), Hwang and Park (2016), Lim et al. (2021), Song et al. (2020), and Wiedmer et al. (2021).

One econometric concern regarding the DID application in my context is that Meijer implemented Shop & Scan in different waves across its stores. Traditionally, the treatment in a DID analysis occurs at one specific time. For my research, however, the treatment schedule is more complex, with stores and city markets treated in waves, as described above.

To address this econometric concern, I use the weighted stacked DID design, a methodology that has been used in past studies, such as Callaway and Sant'Anna (2021) and Sun and Abraham (2021). A weighted stacked DID model is designed to analyze data from a staggered

[17] These stores did not implement Shop & Scan until September 2019.

adoption process (Wing et al. 2024). Each implementation wave includes a treatment subgroup and a control subgroup in what is called a “sub-experiment”.

As depicted in Table 1a and Table 1b, my data spans from February 2017 to December 2018 and consists of two sub-experiments. Two datasets are used in my analysis. The first dataset is used to estimate store traffic, customer dwell time and store visits. The monthly observations are at the store level for Meijer retail outlets. The second dataset is used to estimate monthly average transaction size. This dataset is at the city market level, where an observation consists of average transaction size for Meijer in a city market.

To implement the stacked DID model, I establish event time windows within my data collection period, i.e., sub-experiments, consisting of pre-event and post-event time periods. I specifically designate 9 months preceding and 6 months following the treatments as my observation windows for each sub-experiment. The same event time windows are used for the two sets of estimations.

In the first sub-experiment, the treatment group consists of the initial set of 7 stores (5 city markets) from the first wave of technology adoption, designated as the sub-experiment 1 treated group. These include stores in city markets that were early adopters of the Shop & Scan technology. The control group for this sub-experiment consists of stores (city markets) from the second and third waves, with 81 stores (68 city markets) respectively.

The Shop & Scan program for the first wave commenced in November 2017. The pre-event period for sub-experiment 1 spans from February 2017 (start of our dataset) to October 2017, while the post-event period extends from December 2017 to May 2018. It is important to note that the conclusion of the sub-experiment 1 post-event period in May 2018 precedes the launch of Shop & Scan for the second wave (sub-experiment 2) by one month.

In sub-experiment 2, the second wave, 39 stores located in 29 city markets are treated, while the 42 stores, located in 39 cities, that will eventually be treated in the third wave act as the sub-experiment 2 control group. The Shop & Scan treatment date for sub-experiment 2, the second wave, is June 2018. I designate the pre-event period for sub-experiment 2 from September 2017 to May 2018, and the post-event period from July 2018 to December 2018, allowing for the same time window lengths for the two sub-experiments.

Next, I enumerate the sub-experiments. The sample in each sub-experiment should satisfy the inclusion criteria (Wing et al. 2024): Within each sub-experiment, 1) all treatment units should have a uniform adoption time, 2) the control group should be comprised of units that have not and will not be treated during the sub-experiment event time window, ensuring an uncontaminated post-period, and 3) all data points in a sub-experiment must fall within its designated event window.

For estimation purposes, I merge the datasets from the two sub-experiments. As shown in Table 1a and Table 1b, both sub-experiments have the same event window lengths, spanning 9 months pre-treatment and 6 months post-treatment. Note that the 39 stores located in 29 cities, treated in the second wave, are present in both sub-experiment 1, acting as a component of the control group, and sub-experiment 2, serving as the treatment group.

Further, I apply sample weights to reflect the different number of stores (city markets) in the treatment and control groups in each of the sub-experiments. Without weighting, the estimates from the stacked DID model may disproportionately reflect the effects of larger groups (e.g., the number of stores (city markets) vary across the two treatments), potentially leading to biased results. To prevent this and ensure an unbiased analysis, I weight the treatment and control observations in each of the sub-experiments. As with Wing et al. (2024), I use the following weighting scheme for my estimation of store traffic:

$$w_{se} = \begin{cases} 1 & \text{if } T_{se} = 1 \\ \dfrac{N_e^T/N^T}{N_e^C/N^C} & \text{if } T_{se} = 0 \end{cases}$$

where w_{se} denotes the weight for store s in sub-experiment e; T_{se} equals 1 if store s is treated in sub-experiment e and 0 otherwise; N_e^T represents the number of treated stores in sub-experiment e; N^T represents the total number of treated stores in the two sub-experiments; N_e^C is the number of control stores in sub-experiment e; N^C is equal to the total number of control stores in the two sub-experiments. A similar weighting scheme is used for my estimation of city market sales.

To illustrate, in sub-experiment 1 for my traffic estimations, $w_{s1} = 1$ for the treated group and 0.152 (= (7/46)/(81/81)) for the control group, where 46 (= 7+39) is the total number of treated stores across all sub-experiments. The formula adjusts the influence of each group so that each treated store's impact is relative to the total number of treated stores, and each control store's impact is proportional to the total number of control stores, thus normalizing the influence across different group sizes. In sub-experiment 2, $w_{s2} = 1$ for the treated group and 1.635 (= (39/46)/(42/81)) is the weight for the control group. Sample weights for other groups are calculated and reported in Table 1a for the store traffic estimations.

Similarly, I calculate and report the sample weights for the transaction size estimation in Table 1b. Specifically, in sub-experiment 1, $w_{s1} = 1$ for the treated group and 0.152 (= (5/34)/(68/68)) for the control group, where 34 (= 5+29) is the total number of treated city markets across all sub-experiments. In sub-experiment 2, $w_{s2} = 1$ for the treated group and 1.487 (= (29/34)/(39/68)) is the weight for the control group.

After computing the sample weights for the treatment and control groups in the two sub-experiments, each data point is multiplied by its corresponding weight. In the estimation process, coefficients are obtained such that the objective function minimizes the weighted sum of squared residuals rather than the simple sum of squared residuals.

Table 1a. Experiment Design – Store Traffic

Sub-Experiment	Event Window (Months)			Group	Stacked Groups	Store Traffic	
	-9	0	+6			Number of Stores	Sample Weight
1	2017-02	2017-11	2018-05	Treatment	1st Wave	7	1.000
				Control	2nd and 3rd Waves	81	0.152
2	2017-09	2018-06	2018-12	Treatment	2nd Wave	39	1.000
				Control	3rd Wave	42	1.635

Table 1b. Experiment Design – Transaction Size

Sub-Experiment	Event Window (Months)			Group	Stacked Groups	Transaction Size	
	-9	0	+6			Number of City Markets	Sample Weight
1	2017-02	2017-11	2018-05	Treatment	1st Wave	5	1.000
				Control	2nd and 3rd Waves	68	0.147
2	2017-09	2018-06	2018-12	Treatment	2nd Wave	29	1.000
				Control	3rd Wave	39	1.487

4.3. Data Collection

I use data from two primary sources. First, data on average in-store dwell time and consumer store visits are gathered from Placer.ai, a platform that records customer foot traffic by tracking mobile phones. The two metrics are provided at the store-month level for the period February 2017 to December 2018. In-store dwell time represents the average length of stay by a customer during a shopping visit to a store, measured in minutes. Monthly customer store visits are measured by the count of customer store visits during a month.

Second, to test the impact of MCST on consumer transaction size, I utilize a weekly, city-level dataset from Earnest Analytics. Earnest Analytics is a research firm that collects consumer purchase data based on credit card, debit card, and store card records. The platform captures the spending of 6.5 million U.S. consumers who show consistent behavior in card spending, about 0.5% of households in each state.[18] Data from Earnest Analytics has been used in prior research (e.g., Kim and McCarthy 2024; Paraskevas et al. 2024; Wang et al. 2023). The data are used to calculate weekly consumer transaction size for retailers reported at the retailer-city level based on store locations. City markets are defined by administrative boundaries as indicated by the U.S. Census, excluding surrounding suburban areas around a focal city.

I aggregate the weekly Earnest data into city-month observations and include 23 months of Meijer's sales data by city market, from February 2017 to December 2018. I use the natural log transformed value of monthly consumer transaction size to analyze consumer average spending per store visit in a city market for our focal retailer, Meijer.

Similar store-level foot traffic data and/or firm market-level sales data have been used in past studies. Li and Wang (2024) investigated how partnerships with delivery platforms can benefit restaurants. They found that restaurant sales increase after forming partnerships, with differential impacts depending on restaurant format. Pan et al. (2024) examined the impact of store location decisions on foot traffic to the retail locations of warehouse club stores. They found that foot traffic depended on warehouse clubs co-locating with complementary retailers, such as supermarket chains that attract regular, weekly store visits. Following these studies (and others), my research uses store-level foot traffic and city-level sales data to analyze the impact of MCST on retailer performance outcomes.

[18] Data are only collected from active shoppers. If consumers stop using their credit cards, they are dropped from the dataset.

4.4. Variable Definitions

4.4.1. Store-level analysis focusing on store traffic

I use two dependent variables to assess store traffic performance, the logged value of average in-store dwell time in minutes and the logged value of monthly store visits. Average in-store dwell time ($DWEL\_TIME_{semy}$) represents customers' average length of stay in minutes at store s in month m of year y in sub-experiment e. Total store visits ($STOR\_VSIT_{semy}$) is the count of total customer visits at store s in month m of year y in sub-experiment e.

Based on the weighted stacked DID model, my treatment is the implementation of Shop & Scan in a sub-experiment ($SHOP\_SCAN_{se}$). The treatment effect is a dummy variable equal to 1 if store s is in the treatment group in sub-experiment e. Otherwise, it is equal to 0. In addition, I use a dummy variable for post-treatment months during the event windows ($POST_{emy}$) to distinguish between the pre- and post-treatment periods. This variable is equal to 0 during the pre-treatment periods and 1 in the post-treatment periods of each of the sub-experiments.

I add three variables to control for market characteristics. The first is the population in a trade (market) area ($AREA\_POP_{semy}$).[19] This variable is equal to the population in the trade area where store s is located in month m of year y in sub-experiment e. Information for trade areas is provided by Placer.ai. The second control variable is household median income of a trade area ($AREA\_INC_{semy}$). This variable is equal to the median income of households in the trade area where store s is located in month m of year y in sub-experiment e. The last control variable is the physical size of a trade area ($AREA\_SIZ_{semy}$). This variable is equal to the square miles of the trade area where store s is located in month m of year y in sub-experiment e.

[19] Trade areas are calculated by Placer.ai, representing the volume of traffic reaching the venue or complex. Details can be found at https://docs.placer.ai/reference/post_v1-reports-true-trade-area.

I add another control variable, consumer sentiment index ($SEN\_INX\_T_{my}$), to control for changes in consumer behavior due to changing economic circumstances. The consumer sentiment index is generated by the University of Michigan, with representations for consumer confidence in month m of year y compiled on a national basis.[20] I add fixed store effects and month fixed effects to control for store-level characteristics and seasonality respectively. Finally, ϵ_{semy} is a random error term in my model. Equation (1) shows my model.

$Ln(DWEL\_TIME_{semy})$ $Ln(STOR\_VSIT_{semy})$	$=\beta_0 + \beta_1 \cdot SHOP\_SCAN_{se} + \beta_2 \cdot POST_{emy} + \beta_3 \cdot SHOP\_SCAN_{se} \cdot POST_{emy} + \beta_4 \cdot AREA\_POP_{semy} + \beta_5 \cdot AREA\_INC_{semy} + \beta_6 \cdot AREA\_SIZ_{semy} + \beta_7 \cdot SEN\_INX\_T_{my} + \beta_8 \cdot STORE_s + \beta_9 \cdot MONTH_m + \epsilon_{semy}$ Equation (1)

4.4.2. Market-level analysis focusing on transaction size

Following Perdikaki et al. (2012), I measure consumer transaction size using log value of average transaction size, $Ln(TRAN\_SIZE_{cemy})$, representing the log values of average transaction size in city c in month m of year y in sub-experiment e.

$SHOP\_SCAN_{ce}$ represents the adoption of Shop & Scan in stores in a city market. If one store in city c has implemented Shop & Scan technology, this variable is set equal to 1.[21] Otherwise, it is equal to zero. I use a dummy variable for the post-treatment windows ($POST_{emy}$) to distinguish pre- and post-treatment periods. This variable is equal to 0 in pre-treatment periods and 1 in post-treatment periods.

[20] This index is generated through consumer surveys and normalized to have a value of 100. Survey questions can be found at https://data.sca.isr.umich.edu/technical-docs.php (Accessed in May 2024)
[21] In my dataset, Meijer implemented Shop & Scan simultaneously across all stores in cities, with one exception. Grand Rapids has six stores within the city. In the first wave the technology was implemented in two stores and in the second wave in four stores. In my main model, Grand Rapids is treated in the first wave. We also conduct a robustness check by partially treating Grand Rapids. In the robustness check, I set $SHOP\_SCAN_{ce}$ equal to 0.33 (=2/6) for Grand Rapids in the first wave. The results are consistent, suggesting robustness of my main model.

I include city-level population (CTY_POP_{cemy}) and household median income (CTY_INC_{cemy}) as control variables. City-level size is not included in this model since it does not change over the timeframe of my estimation. $SEN\_INX\_S_{my}$ represents a month-level consumer sentiment index. $CITY_c$ and $MONTH_m$ are city and month fixed effects, and ϵ_{cemy} is a random error term. See Equation (2).

$Ln(TRAN\_SIZE_{cemy})$	$= \beta_0 + \beta_1 \cdot SHOP\_SCAN_{ce} + \beta_2 \cdot POST_{emy} + \beta_3 \cdot SHOP\_SCAN_{ce} \cdot POST_{emy} + \beta_4 \cdot CTY\_POP_{cemy} + \beta_5 \cdot CTY\_INC_{cemy} + \beta_6 \cdot SEN\_INX\_S_{my} + \beta_7 \cdot CITY_c + \beta_8 \cdot MONTH_m + \epsilon_{cemy}$ Equation (2)

Table 2 presents summary statistics for my variables, and Table 3 and Table 4 report correlation matrices for the store traffic and sales models, respectively.

Table 2. Summary Statistics

Variables	Unit	# of obs.	Mean	Std. Dev.	Min	Max
$DWEL\_TIME_{semy}$	Minutes	2,658	45.47	3.45	34	65
$STOR\_VSIT_{semy}$	Count	2,658	162,163	32,414	84,791	299,261
$SHOP\_SCAN_{se}$	Dummy	2,658	0.27	0.45	0	1
$POST_{emy}$	Dummy	2,658	0.40	0.49	0	1
$AREA\_POP_{semy}$	10,000 people	2,658	7.88	5.79	0.48	34.50
$AREA\_INC_{semy}$	10,000 Dollars	2,658	5.16	1.10	2.42	8.85
$AREA\_SIZ_{semy}$	10 square miles	2,658	3.78	1.27	1.21	9.64
$SEN\_INX\_T_{my}$	Index	2,658	97.64	2.00	93.40	101.40
$TRAN\_SIZE_{cemy}$	Dollars/Count	1,980	54.46	8.43	15.43	253.13
$SHOP\_SCAN_{ce}$	Dummy	1,980	0.31	0.46	0	1
$POST_{emy}$	Dummy	1,980	0.40	0.49	0	1
CTY_POP_{cemy}	10,000 People	1,980	4.61	8.79	0.11	67.50
CTY_INC_{cemy}	10,000 Dollars	1,980	5.74	1.06	4.37	8.09
$SEN\_INX\_S_{my}$	Index	1,980	97.67	2.03	93.40	101.40

Table 3. Correlation Matrix – Store Traffic

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	$DWEL\_TIME_{semy}$	1.0000							
(2)	$STOR\_VSIT_{semy}$	-0.0276	1.0000						
(3)	$SHOP\_SCAN_{se}$	-0.0103	0.2283***	1.0000					
(4)	$POST_{emy}$	0.1833***	0.1254***	-0.0235	1.0000				
(5)	$AREA\_POP_{semy}$	-0.0328+	0.2675***	-0.2587***	0.0039	1.0000			
(6)	$AREA\_INC_{semy}$	0.0988***	-0.2510***	-0.2239***	-0.0068	0.0442*	1.0000		
(7)	$AREA\_SIZ_{semy}$	0.0254	0.2426***	0.0622**	0.0286	0.0862***	0.0686***	1.0000	
(8)	$SEN\_INX\_T_{semy}$	0.0262	-0.0530**	0.0942***	0.2235***	-0.0054	-0.0059	-0.0023	1.0000

Notes: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001

Table 4. Correlation Matrix – Transaction Size

	Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1)	$TRAN\_SIZE_{cemy}$	1.0000					
(2)	$SHOP\_SCAN_{ce}$	0.2493***	1.0000				
(3)	$POST_{emy}$	0.0169	-0.0000	1.0000			
(4)	CTY_POP_{cemy}	0.1952***	-0.1184***	-0.0001	1.0000		
(5)	CTY_INC_{cemy}	-0.0045	-0.0863***	0.0738**	-0.1145***	1.0000	
(6)	$SEN\_INX\_S_{my}$	-0.0430+	0.0745***	0.2016***	-0.0001	0.0504*	1.0000

Notes: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001

5. Estimation Results

I present my main estimation results in Tables 5 and 6, [22] while the details of the parallel trend tests are provided in Appendix D. Hypothesis 1 argues that mobile consumer scanning technology decreases customer average in-store dwell time. In Model 1.1, the coefficient for $SHOP\_SCAN_{se} * POST_{emy}$ is negative and significant, -0.043 (p<0.001), indicating that a customer's length of stay while shopping decreases by 4.3% on average after the adoption of Shop & Scan technology. This result illustrates that the use of Shop & Scan technology by retailers can lead to a decrease in customer in-store dwell time as proposed by industry managers. Hence, Hypothesis 1 is supported.

Hypothesis 2 states that mobile consumer scanning technology increases total store visits. In Model 1.2, the coefficient of $SHOP\_SCAN_{se} * POST_{emy}$ is positive and significant, 0.045 (p<0.001). This finding suggests that, on average, the introduction of this technology is associated with an increase in monthly store visits by 4.5%, representing the positive demand impact from the technology. Thus, Hypothesis 2 is supported.

Hypothesis 3 states that mobile consumer scanning technology decreases average spend per shopping visit. Using city-level transaction data, I test the impact of MCST technology on

[22] In the weighted stacked DID models, stores that implemented MCST in wave 2 occupy dual roles: they are part of the control group in sub-experiment 1 and the treatment group in sub-experiment 2. Consequently, these wave 2 stores appear twice in my dataset, essentially constituting duplicate observations. Based on Wing et al. (2024), I cluster observations at the store level to account for these duplications.

customer transaction size based on Equation 2. Table 6 reports the results. In Model 2.1, the coefficient for $SHOP\_SCAN_{ce} * POST_{emy}$ is negative and significant, -0.063 (p<0.001). This result indicates that this technology decreases sales volume per store visit by 6.3%, supporting Hypothesis 3.

I perform robustness checks using propensity score matching to address potential endogeneity concerns, notably the introduction of MCST into stores may be systematic rather than random. Details and results of the robustness checks are presented in Appendix E, with major results aligning with those from my main models, thereby suggesting the robustness of my findings. Overall, all my hypotheses are supported. The results verify Meijer's expectations that MCST reduces customers' in-store dwell time and increases total store visits. However, a result that is likely unintended is that MCST reduces consumers' average transaction size, potentially because of the real-time monitoring of total spending enabled by MCST.

Table 5: Results – Store Traffic

	Model 1.1 Ln($DWEL\_TIME_{semy}$)	Model 1.2 Ln($STOR\_VSIT_{semy}$)
$SHOP\_SCAN_{se}$	0.045*** (0.006)	0.023*** (0.006)
$POST_{emy}$	0.031*** (0.003)	0.003 (0.003)
$SHOP\_SCAN_{se}$*$POST_{emy}$	-0.043*** (0.009)	0.045*** (0.007)
$AREA\_POP_{semy}$	0.002+ (0.001)	-0.002** (0.001)
$AREA\_INC_{semy}$	-0.006** (0.002)	0.009*** (0.002)
$AREA\_SIZ_{semy}$	-0.003+ (0.002)	-0.001 (0.002)
$SEN\_INX\_T_{my}$	0.008*** (0.001)	0.003** (0.001)
Store fixed effect	Included	Included
Month fixed effect	Included	Included
N	2,658	2,658
F statistic	80.38***	146.93***
R square	0.3218	0.6632

Notes: Clustered standard errors in parentheses. + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

Table 6: Results – Transaction Size

	Model 2.1 Ln($TRAN\_SIZE_{cemy}$)
$SHOP\_SCAN_{ce}$	0.688*** (0.018)
$POST_{emy}$	0.013 (0.012)
$SHOP\_SCAN_{ce}$* $POST_{emy}$	-0.063*** (0.019)
CTY_POP_{cemy}	0.008*** (0.001)
CTY_INC_{cemy}	0.250*** (0.002)
$SEN\_INX\_S_{my}$	0.001 (0.003)
City fixed effect	Included
Month fixed effect	Included
N	1,980
F statistic	21.47***
R square	0.1614

Notes: Clustered standard errors in parentheses. + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

6. Extended Analyses and Discussion

My study examines the impact of MCST on retailer store traffic and customer transaction size. To further explore the strategic value of MCST, I conduct extended analyses focusing on (1) the origin of increased store visits, (2) changing shopping patterns, and (3) store sales. Detailed results of the extended analyses are provided in Appendix F. Key findings from both the main analyses (Tables 5-6) and the extended analyses (Tables A6-A8 in the appendix) are summarized in Tables 7-9.

6.1. Origin of Increased Store Visits

My findings indicate that, as anticipated, MCST reduces in-store dwell time for customers while increasing monthly store visits. Shoppers can bypass normal check-out lines, thus expediting the check-out and payment processes. Moreover, MCST may boost in-store foot traffic, potentially due to its efficiency and convenience. In this analysis, I explore the origins of the increased customer visits, notably whether the increases come from new customer demand or increases in the frequency of customer visits. Details of this extended analysis can be found in Appendix F1 and are summarized in Table 7.

$Ln(NUM\_CUST_{semy})$ and $Ln(AVG\_VSIT_{semy})$ represent natural log transformed values of number of unique customers and average number of monthly store visits per customer at store s in month m of year y in sub-experiment e. The results of this analysis demonstrate that MCST leads to an increase in both the number of unique customers and the average number of monthly visits per customer, suggesting that the rise in total store visits is due to both a growth in the customer base and an increase in repeat visits.

6.2. Changing Shopping Patterns

My interview with a Meijer assistant store manager (see Footnote 11) revealed that labor shortages motivated the adoption of MCST. If MCST changes shopping patterns, this could have further implications for staffing retail outlets. As a result, I investigate the impact of MCST on the pattern of daily store visits. Details of this extended analysis are shown in Appendix F2, and key findings are summarized in Table 8.

The dependent variables (one for each day of the week) are the number of daily customer visits from Monday to Sunday at store s in month m of year y in sub-experiment e. The results show that MCST leads to a changing shopping pattern, boosting visits on Sundays and Mondays but reducing visits on Tuesdays, Thursdays, Fridays, and Saturdays. Although Meijer management did not provide an explanation for this new pattern, knowledge of the changing shopping habits could help the company improve labor shift planning and customer engagement.

6.3. Store Sales

As noted above, I find that the implementation of MCST results in a reduction in average transaction size (reducing sales) but an increase in store visits (increasing sales). To determine the net effect of MCST on store sales performance, I estimate a model using Meijer's city-level sales,

$Ln(SALES_{cemy})$, as the dependent variable. This variable represents the log value of store sales volume in city c in month m of year y in sub-experiment e. Details of this extended analysis can be found in Appendix F3, and key findings are summarized in Table 9.

As shown in Table 9, although transaction size is reduced following the implementation of MCST, retail sales increase. Thus, the company experiences a net increase in sales following the introduction of the technology despite the lower transaction size, due to the more frequent visits by existing customers and to the increased customer base.

Table 7: Results – Consumer Base and Store Visits[23]

	Model 1.2 Ln($STOR\_VSIT_{semy}$)	Model A1.1 Ln(NUM_CUST_{semy})	Model A1.2 Ln(AVG_VSIT_{semy})
	From Table 5	From Table A6	From Table A6
$SHOP\_SCAN_{se}$*$POST_{emy}$	0.045*** (0.007)	0.053*** (0.008)	0.011* (0.005)

Table 8: Results – Consumer Store Visits during a Week

	Model 1.2 Ln($STOR\_VSIT_{semy}$)	Model A2.1 Ln(MON_VSIT_{semy})	Model A2.2 Ln(TUE_VSIT_{semy})	Model A2.3 Ln(WED_VSIT_{semy})	Model A2.4 Ln(THU_VSIT_{semy})	Model A2.5 Ln(FRI_VSIT_{semy})	Model A2.6 Ln(SAT_VSIT_{semy})	Model A2.7 Ln(SUN_VSIT_{semy})
	From Table 5	From Table A7	From Table A7	From Table A7	From Table A7	From Table A7	From Table A7	From Table A7
$SHOP\_SCAN_{se}$*$POST_{emy}$	0.045*** (0.007)	0.014*** (0.002)	-0.007*** (0.001)	0.001 (0.001)	-0.011*** (0.001)	-0.003** (0.001)	-0.003* (0.001)	0.009*** (0.001)

Table 9: Results – Store Sales Volume

	Model 2.1 Ln($TRAN\_SIZE_{cemy}$)	Model A3.1 Ln($SALES_{cemy}$)
	From Table 6	From Table A8
$SHOP\_SCAN_{ce}$* $POST_{emy}$	-0.063*** (0.019)	0.060** (0.022)

[23] Clustered standard errors are shown in parentheses from Table 7 to Table 9. Significance levels: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

7. Conclusions and Implications

Over the last several decades, the retail sector has undergone a profound transformation driven by advancements in digital technology. These innovations have revolutionized retail operations and services, while substantially altering customer shopping behaviors and expectations. This study explores the role of MCST in modern retail environments, using a case study approach based on the implementation of Meijer's Shop & Scan program. I find that MCST significantly alters store traffic and sales outcomes in both positive and negative directions (from the retailer's perspective).

Similar to Son et al. (2020), a core finding of this research is an adjustment in shopping patterns after the implementation of MCST, representing a significant decrease in time customers spend in-store. Moreover, the enhanced shopping experience resulting from MCST likely contributes to increased frequency of customer visits. These increased store visits (a positive MCST impact to the retailer) offset the lower transaction size after the technology implementation (a negative MCST impact to the retailer), resulting in a net increase in sales from the adoption of the technology.

To deepen the understanding of MCST's value, I analyzed the impact of the technology from multiple perspectives. First, my findings demonstrate that MCST boosts both the number of unique customers and the average visits per customer, indicating that increased store traffic stems from both new patronage and repeat visits. Additionally, the technology may change daily shopping patterns, increasing visits on some days, while reducing visits on others. Finally, while MCST tends to reduce the size of individual transactions, it leads to more frequent store visits, ultimately increasing store sales volume.

7.1. Theoretical Implications

This research makes several theoretical contributions. First, this research contributes to the CL literature by examining how the consumer-centered application, MCST, impacts retail outcomes. Prior research (e.g., Carbone et al. 2017; Ta et al. 2015; Wang et al. 2022) has conceptualized various aspects of CL, such as consumer decision-making, inventory management, and the transformation of consumers into active participants in the logistics process. I investigate how transferring retail logistics activities from store employees to consumers impacts retailer outcomes, in both positive and negative directions.

Second, I expand the literature on retail mobile applications and MCST. While the adoption, use, and performance of mobile applications have been comprehensively analyzed (e.g., Deng et al. 2022; Ghose and Han 2014; Lee et al. 2020; Son et al. 2020; Sun et al. 2019), research addressing MCST remains limited. Previous studies, such as Shi et al. (2021) and Ferreira et al. (2023), explored the information value and consumer acceptance of MCST. My study builds on these insights by examining the effects of MCST on retailer performance, including store traffic and sales, contributing new perspectives to the discourse of this technology.

Finally, I contribute to the understanding of consumer spending patterns from the perspective of price transparency and mental accounting. By providing real-time visibility of total spending, MCST promotes greater price transparency, which influences consumer spending decisions. As shoppers monitor their expenditures, they may become increasingly conscious of their budget limits, potentially reducing spend per shopping visit. Prior research has examined transaction size through various lenses, such as return policies (Wang et al. 2024), consumer emotions (Nichols et al. 2015), product assortment (Mani et al. 2022; Martin et al. 2020), and sales promotions (Ramanathan and Dhar 2010). I extend this understanding by revealing how MCST directly impacts transaction size, offering new insights into how price transparency can reshape consumer spending behavior and purchasing patterns.

7.2. Managerial Implications

First, I show that MCST may improve consumer engagement by providing greater pricing transparency, allowing customers to monitor spending in real-time. This transparency fosters trust and aligns with the growing demand for control over purchase decisions, potentially enhancing customer satisfaction (Marzocchi and Zammit 2006). Moreover, by reducing shopping time and simplifying the checkout process, MCST may lower in-store shopping stress, further improving the customer experience.

Second, I demonstrate the need for retailers to develop strategies to counteract the reduction in transaction size, resulting from the implementation of MCST. Retailers can counter the impact of MCST on transaction size by offering incentives, such as discounts on bundled purchases or tiered rewards for spending thresholds, encouraging higher spending (Jonsson 2023). Real-time, personalized promotions based on shopping history or basket composition can also boost transaction value and strengthen customer loyalty.

Finally, retailers can study how MCST changes shopping patterns to determine staffing requirements and to enhance the customer experience. MCST provides valuable consumer data on basket composition and purchasing patterns, enabling data-driven decision-making in areas such as demand forecasting, human resources, inventory management, and marketing.

7.3. Limitations and Future Research

Despite its contributions, this research has several limitations. First, due to data limitations, I do not track consumer behavior at the individual level. Further research could use individual-level data, such as data from behavioral experiments, to more closely examine the impact of MCST.

Second, my study uses two levels of data to examine how MCST impacts store traffic (location-level data) and retailer sales (city market-level data). Future research could adopt a more harmonized data collection approach to examine the impact of MCST on retail performance.

Third, while Meijer claims that Shop & Scan reduces checkout time, my findings reveal that the technology reduces consumers' average in-store dwell time. However, it remains unclear whether this reduction is primarily driven by shorter checkout durations. Due to data limitations, I was unable to distinguish between the time spent shopping and the time spent waiting at checkout. Future research could focus specifically on consumers' checkout waiting time to determine whether MCST effectively achieves its intended purpose.

Fourth, I focus on Meijer's Shop & Scan implementation opens the door for further investigations into alternative MCST applications, such as Kroger's "Scan, Bag, Go", to see how our results may be generalized across applications. Future studies may also provide a deeper understanding of how various MCST interfaces (i.e., consumer smartphones versus retailer-provided devices) impact shopping behavior and retail operations.

Finally, despite many advantages, retailers encounter several impediments to the adoption of MCST. One major challenge is inventory shrinkage, which could impose financial losses on grocery retailers (Thakker 2019). Thus, one extension of this research could explore the security challenges associated with the implementation of MCST.

Chapter 3: Unlocking Sales Growth: The Dynamic Interplay of Pre-sales Fit Risk Mitigation and Post-sales Fit Risk Recovery Practices

1. Introduction

Fit risk is a major impediment to sales, leading to costly product returns and decreased consumer satisfaction (Hong and Pavlou 2014). Consumers often struggle to visualize how products will look or fit based solely on online images and descriptions, increasing uncertainty and hesitation in purchase decisions (Vidojevic 2024). Additionally, product returns can be costly and logistically complex due to factors like product size, weight, and handling requirements (Narvar Team 2021). To mitigate consumer concerns about fit risk, retailers employ various strategies, including pre-sales fit risk mitigation practices (pre-sales practices) and post-sales fit risk recovery practices (post-sales practices).

In this study, I use the furniture industry as my research context to analyze the effects of pre-sales and post-sales practices. Fit mitigation is important in the furniture retail sector due to its high-value, bulky, products characterized by strong consumer preferences and specific fit requirements. Consequently, furniture retailers have actively adopted various pre-sales and post-sales practices to address and minimize fit risk.

Pre-sales practices encompass activities that customers engage in while navigating their path to a purchase decision (Gustafsson et al. 2021). Traditional methods, such as size charts, provide product information but do not offer fit verification. In recent years, retailers have introduced technological pre-sales practices to further address fit uncertainty.

In the furniture industry, two prominent examples are room planner and augmented reality technology (AR tech). Room planner, a more conventional technology, enables consumers to plan, design, and customize their spaces. Users can select furniture items and create detailed layouts for a single room or an entire home. Figure 1a illustrates an example of a room planner.

By contrast, AR tech represents a more advanced solution, allowing customers to visualize furniture in their homes before making a purchase decision (Talochka 2024). Using AR applications on mobile devices, consumers can overlay digital furniture models onto their physical space, providing a realistic preview of how items would fit. Figure 1b presents an example of AR tech in the furniture industry.

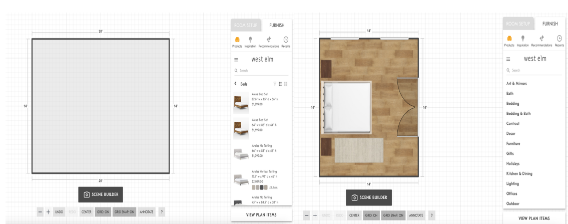
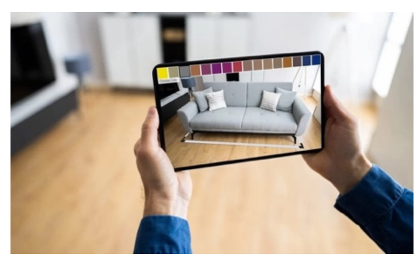
Figure 1a. Example of room planner	Figure 1b. Example of AR tech
	

Figure 1. Examples of Room Planner and AR Tech

Furniture retailers have increasingly adopted technological pre-sales practices, such as room planner and AR tech. Moreover, many retailers also offer online interior designers, human experts who provide customized and personalized recommendations. By incorporating this customized layer of expertise, retailers enhance consumer trust and confidence in their purchasing decisions.

Although room planner, AR tech, and online interior designer are all pre-sales practices that help customers assess product fit in the furniture retail context, they differ in functionality, level of interactivity, and human involvement. Table 1 describes how these three practices are different in five factors.

Table 1. Differences among Three Pre-sales Practices

Practice	Room Planner	AR Tech	Online Interior Designer
Type	Self-service tool	Visualization tool	Human-assisted service
User Involvement	High	Medium	Low
Fit Focus	Spatial	Visual + Spatial	Aesthetic + Functional
Customization	Manual configuration	Real-time overlay	Personalized, curated plans
Technology vs. Human	Fully automated	Fully automated	Human-in-the-loop

Although both technology-based and human-based pre-sales practices help mitigate fit risk, they will not be entirely reliable. Consumers may still find that purchased products do not fit their needs. This underscores the importance of post-sales practices in alleviating consumer concerns. One of the most common post-sales practices is having a lenient return policy. Based on Abdulla et al. (2019), Abdulla et al. (2022), and Janakiraman et al. (2016), return leniency (as outlined in the next section) comprises five key factors: time, monetary, effort, scope, and exchange.

The effect of pre-sales and post-sales practices have been analyzed in prior studies. For example, Wang et al. (2023) found that virtual try-on technology, a pre-sales practice, can serve as a long-term solution for enhancing retailers' sales performance after the COVID-19 pandemic. In addition, Rao et al. (2018) demonstrated that greater return leniency enhances consumers' willingness-to-pay. However, the interaction between pre-sales and post-sales practices, to the best of my knowledge, has not been analyzed. To address this gap, this study analyzes both the direct effects of pre-sales and post-sales practices as well as the interaction between pre- and post-sales policies. Specifically, I examine how these policies influence furniture retailers' sales performance.

My dataset comprises 102 furniture retailers in the United States, sourced from Earnest Analytics. From this platform, I derive U.S.-level monthly sales volume data for furniture retailers from 2018 to 2022. Additionally, I gather information on retailers' adoption of pre-sales and post-sales practices from various public sources, including retailers' archival websites and privacy policies, supplemented by interviews with customer service representatives conducted via retailer websites. Furthermore, since the study period includes the COVID-19 pandemic, I account for the impact of government restrictions on retailers by incorporating the Containment and Health Index (CHI) from the Oxford COVID-19 Government Response Tracker (OxCGRT) into my models.

My analysis reveals that both pre-sales and post-sales practices contribute to an increase in retailers' sales volumes. Further, the relationship between these two types of practices is context dependent. At lower levels of return leniency, the two practices act as complements, jointly enhancing sales performance. However, at higher levels of return leniency, they may function as substitutes, as the presence of one reduces the incremental benefit of the other.

To gain deeper insight into my findings, I conducted several extensions to my analysis. First, I disaggregated return leniency into five factors as mentioned above. My findings indicate that time, monetary, and exchange return leniency positively impact sales performance, while effort and scope do not have a significant effect. Further moderation analysis reveals that instituting room planner can substitute for these post-sales policies. In contrast, instituting AR tech or providing an online interior designer do not consistently substitute for having a lenient post-sales returns policy.

Second, I segmented sales volume into online and offline sales to examine the impact of pre-sales and post-sales practices across different sales channels. My analysis of online sales reveals that while a lenient return policy serves as a strong incentive for customers to complete their purchases, room planner can further enhance online sales performance. Conversely, my analysis of offline sales indicates that online interior designers negatively impact offline sales performance. This finding suggests that online interior design services may encourage consumers to finalize their purchases online, potentially reducing foot traffic and offline transactions.

This study makes several theoretical contributions. By integrating cue dianosticity and signaling theories, I revealed interactions between pre-sales and post-sales practices. I found that pre-sales fit risk mitigation practices, including room planner, AR tech, and online interior designer, significantly enhance online and total retail sales. In addition, online technologies, such as room planner and AR tech, also positively impact offline sales, whereas online interior designers drive online purchases and reduce offline sales. On the other hand, return leniency, as a post-sales practice, positively influences sales; in particular, time, monetary, and exchange factors, while effort and scope leniency do not have a significant impact. Notably, pre-sales and post-sales practices generally act as substitutes.

My findings offer several managerial implications. First, retailers may prioritize return leniency practices to enhance sales, particularly those related to time, monetary, and exchange policies. Second, balancing pre-sales and post-sales investments can effectively mitigate fit uncertainty, reducing reliance on lenient return policies. Finally, room planner and AR tech significantly boost both online and offline sales, suggesting the importance of integrating online trials with in-store experiences.

2. Theoretical Background

Following Gustafsson et al. (2021), I define fit risk as the customer's experience of doubt as to whether a product physically fits. The fit of furniture, as an example of experience goods, can be known only after its purchase and use (Becchetti et al. 2020). As such, pre- and post-sales practices can reduce purchasing risks, ultimately leading to better sales performance.

Similar to Gustafsson et al. (2021), I divide fit risk practices into two types, pre-sales practices and post-sales practices. Pre-sales practices are activities in which customers engage before reaching a purchase decision, while post-sales practices compensate fit risk after purchase decisions (Gustafsson et al. 2021). In this analysis, two technologies and one human-related factor serve as our pre-sales practices while return leniency serves as a post-sales practice. I use cue diagnosticity framework (CDF) and signaling theory to analyze the effect of pre-sales and post-sales practices respectively.

2.1. Pre-sales Fit Risk Mitigation Practices

Pre-sales fit practices provide information about products prior to purchase so that customers can obtain a better understanding of the product to make an informed purchase decision (Gustafsson et al. 2021). Online pre-sales practices bridge the gap between the physical and digital retail environments by conveying detailed, relevant, and contextual product information online. According to CDF, consumers rely on diagnostic cues from product information to form accurate perceptions and make informed decisions (Purohit and Srivastava 2001). Practices such as online reviews and size charts, chat bots, and online fit technologies act as diagnostic cues, enabling consumers to assess how well products suit their needs in terms of size, appearance, compatibility, or functionality, thus supporting informed purchase decisions (Minnema et al. 2016).

Providing fit-related diagnostic cues through online channels can offset product returns by delivering accurate and valuable information (De Leeuw et al. 2016; Hjort et al. 2019). However, some cues provided may have limited diagnosticity, thus reducing their usefulness (Gustafsson et al. 2021). For instance, online reviews reflect subjective experiences that may not generalize across consumers, while size charts may fail to account for individual variations.

To further enhance fit, retailers have adopted technological pre-sales practices, capable of providing rich, interactive, and personalized fit-related diagnostic cues. These technologies include style recommendation engines, 3D product visualization, virtual try-on (VTO) systems, and AR tech. The technologies can provide style recommendations, fit visualization, and fit recommendations (Miell et al. 2018).

The impact of technological pre-sales mitigation practices as diagnostic cues has been analyzed in previous studies. For example, Wang et al. (2023), using department store industry data, empirically tested the impact of virtual try-on technology during the COVID-19 pandemic. The authors found that this technology enhanced retailer sales during the pandemic and could prove useful once the pandemic ended.

Human-based pre-sales fit risk mitigation practices, such as live chat with product experts, virtual consultations, or online interior designers, can also serve as highly diagnostic cues that reduce fit uncertainty. Human experts can engage in two-way, personalized conversations to determine consumer preferences, needs, and contextual constraints. An interactive approach allows for tailored guidance, helping consumers navigate product information, resolve doubts, and receive recommendations that align with expectations. Prior research suggests that personalized interactions foster trust, enhance perceived service quality, and create a sense of reassurance in purchase decisions (Hegner et al. 2019; Riegger et al. 2021). Importantly, human input complements the capabilities of technology by translating abstract visualizations or recommendations into actionable insights that make it easier for consumers to interpret and apply (Lurie and Mason 2007).

Collectively, both technology-based and human-based pre-sales fit risk mitigation practices enhance shopping confidence by improving the diagnosticity of product cues. By reducing perceived risks associated with product misfit, these practices increase certainty in customer decisions, ultimately encouraging purchase completion. For retailers, this translates into improved sales performance. Hence, I posit:

Hypothesis 1: *Pre-sales fit risk mitigation practice increases retailers' sales performance.*

2.2. Post-sales Fit Risk Recovery Practices

Post-sales practices are employed by retailers to provide assurance to consumers that a "bad fit" will not result in a loss; for example, by compensating the customer or fixing the bad fit. A key post-sales practice is a retailer's return policy (Gu and Tayi 2015; Janakiraman et al. 2016). Gustafsson et al. (2021) refer to a return policy as a *post-sales fit uncertainty mitigation practice*. We redefine the term as *post-sales fit risk recovery practice*. This revision reflects the shift in focus from uncertainty, which exists prior to the purchase, to how retailers address misfit or customer dissatisfaction after a sale.

Signaling theory posits that return policies serve as signals that communicate retailer confidence in product quality and commitment to customer satisfaction (Spence 1973). Retailers use lenient return policies to relieve consumer risks, with the intent to increase demand (Greatorex and Mitchell 1994; Gustafsson et al. 2021). All types of retailers, including department stores, specialty stores, and single outlet stores, use these policies to generate demand (Davis et al. 1998), although they may also increase product returns (Petersen and Kumar 2010).

According to the literature (Abdulla et al. 2019, Abdulla et al. 2022, Janakiraman et al. 2016), there are five factors that constitute return leniency: time, monetary, effort, scope, and exchange. Time leniency refers to the deadline (return window) as specified in a retailer's return policy. Longer return windows are regarded as more lenient to consumers. Studies have shown that time leniency impacts purchase decisions. Wang et al. (2023) found that department stores that extended return windows during the COVID-19 pandemic offset sales losses from the pandemic. Rao et al. (2018), using data from eBay online auctions, found that return time leniency increases consumers' willingness-to-pay (WTP), however, the increase in WTP diminishes over time. Ertekin and Agrawal (2020), using data from a jewelry retailer, found that offline sales decreased by 8% when the return window was reduced from 100 days to 60 days.

A retailer's monetary return policy refers to whether customers may receive refunds if purchases are returned. "Restocking fees" or "shipping and handling fees" imposed on returns reduce the leniency of a retailer's monetary returns policy (Abdulla et al. 2019; Janakiraman et al. 2016). Wood (2001) and Wang (2009) found that a full refund policy increases purchases and does not result in higher return rates, compared to a partial refund policy, suggesting benefits from a lenient monetary returns policy. Patel et al. (2021), using order-level data from an online fashion retailer in Sweden, found that the introduction of "free returns" increased orders by 9.15%, product variety per order by 8.74%, and gross margin per order by 9.71%. However, they also found that returns increased by 7.86%.

Effort leniency refers to consumer efforts required to execute returns. For example, requiring customers to produce an original purchase receipt may increase the effort required to return an item. Janakiraman and Ordóñez (2012) conducted a lab experiment to examine the moderating effect of effort leniency on the relationship between time leniency and return rates. They found that when less effort is required, shorter return windows lead to higher return rates. However, if increasing effort is required, shorter return windows lead to lower return rates. Hsiao and Chen (2014) compared effort and monetary leniency. They found that although a "hassle-free" return policy can be cost-effective for a retailer, a money-back guarantee gives the seller more flexibility in developing an effective return policy. Lee and Rhee (2018) also considered effort and monetary leniency and found that the optimal return policy is a hassle-free policy with a partial refund equal to a product's salvage value.

Scope leniency refers to the extent of products sold by a retailer that can be returned. For example, products purchased on sale may not be eligible to return, or only defective products may be returned. Using six years of data on purchases and product returns from an apparel and accessories retailer, Petersen and Kumar (2010) identified the impacts of scope leniency. They differentiated between two categories of scope leniency: all products could be returned (lenient scope return policy) and only defective products could be returned (restrictive scope return policy). Their findings suggested that a lenient scope return policy has a positive impact on returns with the average dollar amount of returns higher under the lenient policy.

Exchange leniency refers to whether products can be returned for cash or only for credit. Cash refunds can be regarded as more lenient than credit-only refunds. Wood (2001) found that a lenient exchange return policy increased purchases with no significant impact on returns, compared to restrictive exchange return policy. Fan et al. (2022) developed a model for a retailer, where the retailer must decide on the cash refund fraction of the product price. They found that cash return policies provide retailers with greater flexibility to prevent wardrobing, a form of fraud where consumers use items briefly and return them for a full refund, effectively "renting" the items for free (Scrancher 2025). On the other hand, Khouja and Hammami (2023) found that that a store credit refund policy reduced fraudulent or exploitive returns.

Based on the literature, applying a lenient return policy should signal quality and commitment, thereby contributing to higher sales. Therefore, I hypothesize:

Hypothesis 2: *Post-sales fit risk recovery practice increases retailers' sales performance.*

2.3. Interaction between Pre-sales Fit Risk Mitigation and Post-sales Fit Risk Recovery Practices

I further combine CDF and signaling theory to analyze the relationship between pre-sales fit risk mitigation practices and post-sales fit risk recovery practices. These two theories are complementary, with signaling theory focuses on the sender's actions and CDF emphasizing the receiver's interpretation of these signals. Specifically, when a firm sends a signal, CDF helps predict whether consumers perceive it as trustworthy and subsequently act upon it.

CDF discusses how consumers evaluate products based on available informational cues and how they determine the diagnosticity from those cues (e.g., their usefulness in differentiating among choices and making informed decisions) (Purohit and Srivastava 2001). Studies have leveraged CDF to analyze how consumers perceive value to make purchasing decisions by examining the relative diagnositicity of different cues. For example, Agrawal et al. (2015) found that the presence of a remanufactured product from an original equipment manufacturer (OEM) serves as an informational cue that influences consumer perceptions of new products. Specifically, the remanufactured product from the OEM acts as a negative diagnostic cue that diminishes the perceived value of new products by up to 8% due to consumer uncertainty over the quality of products sold by the OEM.

Through analytical modelling, Li et al. (2019) argued that consumers evaluate product quality as an informational cue when making their purchase decisions. Moreover, if consumers experience a product failure, the negative diagnostic cue significantly lowers their valuation of the product. Using a two-period model, they found that when the manufacturer has a low-quality reputation but seeks to promote a high-quality product, it is optimal for the firm to provide warranty compensation exceeding the original purchase price.

Childs and Jin (2020) focused on how consumer urgency to buy is influenced by two key diagnostic cues: limited editions and brand-retailer fit. Using experimental studies, they found that limited editions serve as a scarcity-based diagnostic cue, enhancing urgency by signaling exclusivity and rarity. Similarly, a high perceived fit between the retailer and the brand strengthens the cue's diagnosticity by increasing consumer confidence in the product's value.

Signaling theory posits that retailers can use cues to reduce information asymmetry between retailers and consumers, signaling positive characteristics (Abdulla et al. 2022). An example of a retailer's signal is its return policy. Consumers may interpret the return policy as a signal of a retailer's overall quality (Bonifield et al. 2010; Rao et al. 2018; Suwelack et al. 2011; Wood 2001).

Studies have used signaling theory to analyze the effect of return leniency on consumer purchasing intentions. For example, Rao et al. (2018) used signaling theory to investigate the effect of return time leniency. Longer return windows, a positive signal, improved consumers' willingness-to-pay but the positive effect diminished with the increase in time leniency.

Abdulla et al. (2022) used signaling theory to analyze the effect of return leniency on perceived service quality. They found that offering a full refund as part of the return service signaled the retailer's understanding of consumer needs and commitment to absorbing the risk associated with product fit and valuation uncertainty (Abdulla et al. 2019), thereby significantly enhancing the perceived quality of the return service (Abdulla et al. 2022).

In this study, pre-sales fit risk mitigation practices and post-sales fit risk recovery practices serve as key informational cues that influence purchase confidence. According to CDF, consumers evaluate products by relying on available cues, with diagnosticity determining which cues are most influential in shaping perceptions and decisions (Purohit and Srivastava 2001). Additionally, signaling theory suggests that firms strategically provide signals to reduce uncertainty, reassuring consumers about product quality and service reliability (Spence 1973). Although the effect of pre-sales diagnostic cues or post-sales recovery signals has been analyzed by past studies (e.g., Ertekin and Agrawal 2020; Rao et al. 2018; Wang et al. 2023), the interaction between these two practices remains unexplored in prior research.

CDF predicts that consumers prioritize diagnostic cues when making purchase decisions. Advanced pre-sales fit risk mitigation practices offer fit assessments before purchase (Gustafsson et al. 2019; Miell et al. 2018). As a result, these pre-sales cues serve as diagnostic sources of information, reducing uncertainty before a transaction occurs. Consequently, consumers who perceive a product's fit as highly certain prior to purchase may no longer consider post-sales leniency as a necessary factor in their decision making. If a retailer offers pre-sales cues, consumers may place less emphasis on post-sales return policies as a risk-reducing mechanism. Thus, return leniency loses its marginal value in influencing sales when pre-sales practices mitigate fit risk. This logic aligns with prior research showing that consumers adjust their reliance on cues based on their perceived informativeness (Agrawal et al. 2015; Childs and Jin 2020; Li et al. 2019). When pre-sales fit verification is robust, consumers assign lower diagnosticity to return leniency, reducing its ability to further enhance sales.

On the other hand, consumers prioritize cues that they perceive as most diagnostic in reducing uncertainty and guiding decisions. A lenient return policy serves as a post-sales cue that reduces the perceived risk of making a poor fit choice. This signal not only increases purchase confidence but may also diminish the need for consumers to engage in pre-sales fit risk mitigation practices. If consumers know they can easily return a product without penalty, they may perceive less value in investing time or effort in pre-purchase evaluation tools.

Signaling theory suggests that firms can strengthen consumer trust by providing multiple reinforcing signals that reduce perceived risk at different stages of the purchase journey (Spence 1973). From this standpoint, a lenient return policy sends a powerful signal of retailer confidence in the product and a willingness to assume responsibility for potential mismatch (Guo et al. 2024). This post-sales signal alleviates consumer concerns about fit and value, making pre-sales support less critical in shaping the purchase decision. In other words, when return policies are lenient, they can act as a substitute for pre-sales fit mitigation policies.

Based on these observations, pre-sales and post-sales practices may act as substitutes, where reliance on one diminishes the necessity of the other. Therefore, I posit:

Hypothesis 3: *Pre-sales fit risk mitigation practices and post-sales fit risk recovery practices serve as substitutes in influencing retailers' sales performance.*

3. Methodology

In this section, I explain the rationale for selecting furniture industry as the subject area for my research, describe the data and research model, and address potential endogeneity concerns.

3.1. Research Context

I select the furniture industry as the subject area for my research, given the importance of pre-sales fit risk mitigation and post-sales fit risk recovery for high-valued products that often come with strong customer preferences and fit requirements. In the pre-sales phase, many furniture retailers have implemented technology-based and human-based pre-sales fit risk mitigation practices in their operations. Two technologies, in particular, are used to mitigate pre-sales fit risk: room planner and AR tech.

Room planner allows consumers to plan, design, and customize spaces. Consumers can choose furniture items and create detailed room layouts for a single room or an entire house. Its benefits have been discussed in the business press, and include, eliminating purchase risk, enhancing consumer engagement, improving customer experience, reducing returns, developing new customers, and encouraging add-on sales (Hansen 2015; Jameson 2024).

AR tech, an advanced AI technology, is less adopted by furniture retailers but has gained increased academic attention. AR is a system that enhances the real world by superimposing computer-generated information on top of the real world (Furht 2006). This technology has been used in many retail fields, such as shoes and cosmetics (Klavins 2023), but is less prevalent in the furniture sector.

AR technology in the furniture sector provides consumers with an immersive experience, simulating a virtual home to help organize furniture layout (Sandu and Scarlat 2018, Qu and Aflatoony 2022). AR tech can reduce the time and effort needed to purchase furniture, reducing requirements to visit physical stores (Satre et al. 2022).

Technological design services, such as room planner and AR tech, enable consumers to visualize products in their home environments, reducing the cognitive burden, and increasing decision confidence. However, in addition, furniture retailers also employ online interior designers – human experts to offer personalized suggestions and recommendations. Online interior designers can accommodate consumer preferences, providing an additional layer of trust and assurance for customers (Hegner et al. 2019). Thus, online interior designers may also play a key role in reducing pre-sales uncertainty by offering customized suggestions that align with consumers' needs and preferences.

Post-sales fit risk recovery is also important for furniture retailers. Returns in the furniture industry are both challenging and strategically important due to unique logistical and consumer-related factors. The bulky and heavy nature of furniture make returns complex, costly, and resource-intensive, involving high transportation expenses and significant storage requirements (Alidaee et al. 2023). Despite these challenges, returns may be important as they can influence customer satisfaction, loyalty, and purchase decisions by reducing consumer risk (Confente et al. 2021). Furthermore, effective return management can enhance omnichannel strategies, provide competitive differentiation, and offer valuable insights into product improvements, ultimately impacting long-term profitability and sales performance (Karlsson et al. 2023).

Overall, pre-sales fit risk mitigation practices (room planner, AR tech, and online interior designer) and post-sales fit risk recovery practices (lenient return policies) play significant roles in the furniture industry. While previous studies have examined the direct effects of these practices (e.g., such as Gustafsson et al. 2021; Rao et al. 2018; and Wang et al. 2023), their interaction remains largely unexplored. In this study, I specifically focus on the furniture industry to investigate the interplay between pre-sales and post-sales practices.

3.2. Data

I collect data from multiple sources. My sales data are from Earnest Analytics, a market research firm that collects consumer spending data based on the purchase records of credit cards, debit cards, and store cards. Earnest Analytics tracks spending of nine million consumers across the U.S. who have consistent purchasing behavior, about 0.75% of households in each state. If a consumer stops using credit cards, the firm will drop this consumer from their dataset. The data includes monthly online, offline, and total sales for retailers at the national level.

There are 192 furniture companies in the Earnest Analytics database. I exclude 77 companies that sell single merchandise items, such as mattresses or picture frames, since these companies may not have the motivation to adopt room planner, AR tech, or online interior designers. Another 13 companies are excluded; five that are rent-to-buy companies and eight are retailers that closed or merged during our research period. Finally, 102 companies remain, with data from 2018 to 2022.

Information on the timing and use of room planner, AR tech, and online interior designer are collected using the following approaches: First, I determine whether these practices are indicated on retailer websites. I use three approaches to verify the start date of each service listed. First, I use an archive website (https://web.archive.org) to determine when the practice first appeared on a retailer's homepage. If an archival homepage is not available, I search the archival website to find the first time a service is mentioned in the privacy policy. If further clarification is required, I communicate with customer service representatives through human chat or email to inquire about the start date. Finally, I search for press release announcements on retailer websites and public news articles on the Internet to determine start dates.

3.3. Variables and Econometric Model

My dependent variable is a retailer's monthly sales volume. The variable, $SALES_{rmy}$, is defined as retailer r's sales volume in the U.S. in month m of year y.

I use three variables to assess a retailer's pre-sales fit risk mitigation practices. The first is room planner, RM_PLAN_{rmy}, a dummy variable that measures the availability of room planner on a retailer's website. If retailer r provides room planner on its website in month m of year y, this variable is equal to 1. Otherwise, it is equal to 0.

The second variable is AR technology, AR_TECH_{rmy}. AR_TECH_{rmy} is equal to 1 if retailer r provides AR technology in month m of year y. Otherwise, it is equal to 0.

The third pre-sales fit mitigation variable is online interior designer, ON_DSN_{rmy}, assessing whether a retailer has an online designer to provide customized services. This variable is equal to 1 if designers are available for retailer r in month m of year y. Otherwise, it is equal to 0.

I use return leniency to measure post-sales fit risk recovery practices. RET_LEN_{rmy} is a count variable that contains five factors, time (TIM_LEN_{rmy}), monetary (MON_LEN_{rmy}), effort (EFF_LEN_{rmy}), scope (SCO_LEN_{rmy}), and exchange (EXC_LEN_{rmy}). TIM_LEN_{rmy} is a dummy variable that measures a retailer's time return leniency. If a retailer r's return window is longer than the variable's mean value (34 days) for month m of year y, it is equal to 1. Otherwise, it is equal to 0.

MON_LEN_{rmy} examines whether a retailer offers a full refund for a product return. If a retailer r provides a full refund in month m of year y, it is equal to 1. If a retailer r does not provide a full refund or charges a return shipping fee in month m of year y, it is equal to 0.

EFF_LEN_{rmy} examines the effort return leniency of a retailer. This dummy variable is equal to 1 if retailer r does not require an original purchase receipt for a product return in month m of year y. Otherwise, it is equal to 0.

SCO_LEN_{rmy} is a dummy variable measuring a retailer's scope return leniency. This variable is equal to 1 if retailer r accepts all-product return in month m of year y. Otherwise, it is equal to 0.

EXC_LEN_{rmy} is a dummy variable examining whether cash refunds are allowed. If a retailer r allows cash refunds in month m of year y, this variable is equal to 1, and 0 otherwise. My independent variable, RET_LEN_{rmy}, is equal to the sum of these five factors for retailer r in month m of year y.

I add several control variables to my model. The first is containment and health index (CHI_{my}) collected from the Oxford Martin School. Since my data spans from 2018 to 2022, I control for the impact that the COVID-19 pandemic may have had on furniture retail sales in month m of year y. CHI_{my} measures policy responses to the pandemic and contains seven factors, including school closures, workplace closures, travel bans, testing policies, contact tracing, face coverings, and investments in vaccines (Hale et al. 2022). This variable spans from 0 to 100, with 0 implying no containment and health policy in effect and 100 signaling the strictest policy.

The second control variable is a retailer's number of stores in the U.S. (NUM_STR_{rmy}). This variable measures the number of physical stores a retailer r has in month m of year y.

The third control variable is firm age (FIR_AGE_{ry}), equal to the age of retailer r in year y. I include this control variable since older firms may have established customer relationships and reputations and better market knowledge that can positively impact sales volume (Yli-Renko et al. 2001). On the other hand, younger firms may be more innovative, potentially increasing sales if they disrupt markets (Coad et al. 2016).

Table 2 and Table 3 report the summarized statistics and correlation matrix respectively.

Table 2. Statistics Summarization

Variables	Unit	Mean	Std. Dev.	Min	Max
$SALES_{rmy}$	Dollar	513,532	1,228,147	7	14,473,534
RET_LEN_{rmy}	Count	2.13	0.65	1	5
RM_PLAN_{rmy}	Dummy	0.17	0.38	0	1
AR_TECH_{rmy}	Dummy	0.05	0.21	0	1
ON_DSN_{rmy}	Dummy	0.30	0.46	0	1
CHI_{my}	Index	32.14	28.31	0	69.29
NUM_STR_{rmy}	Count	86.90	180.97	0	2,010
FIR_AGE_{ry}	Year	45.07	33.68	0	137

Table 3. Correlation Matrix

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	$SALES_{rmy}$	1.0000							
(3)	RM_PLAN_{rmy}	0.1281***	1.0000						
(4)	AR_TECH_{rmy}	0.1840***	0.0574***	1.0000					
(5)	ON_DSN_{rmy}	-0.0748***	0.1563***	0.0881***	1.0000				
(2)	RET_LEN_{rmy}	0.1671***	-0.0332*	0.1577***	0.0479***	1.0000			
(6)	CHI_{my}	0.0472***	-0.0312*	0.1600***	0.0547***	0.0784***	1.0000		
(7)	NUM_STR_{rmy}	0.5116***	0.0972***	0.0327*	0.0791***	-0.0320*	-0.0186	1.0000	
(8)	FIR_AGE_{ry}	0.0606***	-0.0908***	0.2482***	0.0093	0.0234	0.0174	0.2110***	1.0000

Notes: * p<0.05, **p<0.01, *** p<0.001.

Based on Wooldridge (2010) and Negi and Wooldridge (2020), I adopt a retailer-month fixed effect Poisson regression as my primary estimation model. Poisson regression is well-suited for my analysis because it effectively manages skewed, non-count dependent variables and mitigates issues associated with numerous small nonzero values in my sales dataset (Gould 2011; Wooldridge 2010). Additionally, I conduct a robustness check using a log-linear regression model. I propose our model as follows:

$$SALES_{rmy} = \beta_0 + \beta_1 * RM\_PLAN_{rmy} + \beta_2 * AR\_TECH_{rmy} + \beta_3 * ON\_DSN_{rmy} + \beta_4 * RET\_LEN_{rmy} + \beta_5 * RM\_PLAN_{rmy} * RET\_LEN_{rmy} + \beta_6 * AR\_TECH_{rmy} * RM\_PLAN_{rmy} + \beta_7 * ON\_DSN_{rmy} * RET\_LEN_{rmy} + \beta_8 * CHI_{my} + \beta_9 * NUM\_STR_{rmy} + \beta_{10} * FIR\_AGE_{ry} + \beta_{11} * RETAILER_r + \beta_{12} * MONTH_m + \beta_{13} * YEAR_y + \varepsilon_{rmy}$$

In the model, β_1, β_2, and β_3 examine the direct effects of pre-sales practices, including room planner, AR tech, and online interior designer, while β_4 measures the direct effect of post-sales practices (return leniency). β_5, β_6, and β_7 examine the interaction effects between pre-sales and post-sales practices. $RETAILER_r$, $MONTH_m$, and $YEAR_y$ represent fixed effects of retailer, month, and year to deal with unobserved characteristics, such as brand loyalty, pricing strategy, and seasonality. Finally, ε_{rmy} is a random error term.

3.4. Endogeneity

Offering room planner, AR tech, online interior designer, and lenient return policy may be endogenous with respect to a retailer's sales performance due to the presence of reverse causality. For example, return leniency can affect sales performance, while retailers with better sales performance may be more likely to offer a lenient return policy.

Following the methodology of Miguel et al. (2004), I address potential endogeneity using an instrumental variable (IV) approach. A valid IV should be correlated with the endogenous variable but uncorrelated with the error term. In my analysis, I use the average of room planner, AR tech, online interior designer, and return leniency of other retailers (excluding focal retailer r) in month m of year y as the IV. Similar IVs have been used in the past, such as Brymer et al. (2024), Ghose et al. (2012), Hausman (1996), Paraskevas et al. (2024), and Petrin and Train (2010). Details of the first-stage analysis are provided in Appendix G.

The Cragg-Donald Wald F statistics in the first stage estimation are significantly higher than the Stock-Yogo critical value, rejecting the null hypothesis that the instrumental variables are weak. The under-identification tests using the

Kleibergen-Paap rk LM statistic are highly significant, rejecting the null hypothesis that the equations are under identified (Kleibergen and Paap 2006).

$$RM\_PLAN\_IV_{rmy} = \frac{1}{R-1}\sum_{r_1=1}^{R} RM\_PLAN_{r_1,my}(r_1 \neq r)$$
$$AR\_TECH\_IV_{rmy} = \frac{1}{R-1}\sum_{r_1=1}^{R} AR\_TECH_{r_1,my}(r_1 \neq r)$$
$$ON\_DSN\_IV_{rmy} = \frac{1}{R-1}\sum_{r_1=1}^{R} ON\_DSN_{r_1,my}(r_1 \neq r)$$
$$RET\_LEN\_IV_{rmy} = \frac{1}{R-1}\sum_{r_1=1}^{R} RET\_LEN_{r_1,my}(r_1 \neq r)$$

4. Estimation Results

I present my estimation results in Table 4. Since my results are consistent across models, I use Model 1.1 to interpret the direct effects of pre-sales and post-sales practices and Model 1.5 to interpret moderating effects. Hypothesis 1 argues that pre-sales fit risk mitigation practices increase a retailer's sales performance. In Model 1.1, the coefficients for RM_PLAN_{rmy}, AR_TECH_{rmy}, and ON_DSN_{rmy} are positive and significant, 0.019 ($p<0.001$), 0.042 ($p<0.001$), and 0.980 ($p<0.001$). These findings suggest that pre-sales fit risk mitigation practices, including room planner, AR tech, and online interior designer, increase a retailer's sales volume. Hypothesis 1 is supported.

Hypothesis 2 argues that post-sales fit risk recovery practices increase a retailer's sales performance. In Model 1.1, the coefficient for RET_LEN_{rmy} is positive and significant, 0.852 ($p<0.001$). This finding indicates that a lenient return policy increases a retailer's sales performance. Hence, Hypothesis 2 is supported.

Hypothesis 3 posits that pre-sales fit risk mitigation practices and post-sales fit risk recovery practices serve as substitutes in influencing a retailer's sales performance. In Model 1.5, the coefficients for $RM\_PLAN_{rmy} * RET\_LEN_{rmy}$, $AR\_TECH_{rmy} * RET\_LEN_{rmy}$, and $ON\_DSN_{rmy} * RET\_LEN_{rmy}$ are negative and significant, -0.347 (p<0.001), -0.073 (p<0.001), and -0.098 (p<0.001). These results indicate that pre-sales practices, including room planner, AR tech, and online interior designer, substitute for the post-sales practice of return leniency in their impact on a retailer's sales performance. Thus, Hypothesis 3 is supported.

The results from the control variables reveal that firms with a greater number of physical stores and a longer market presence tend to achieve higher sales performance. In Model 1.1, the coefficients for NUM_STR_{rmy} and FIR_AGE_{ry} are both positive and significant, 0.000 (p<0.001) and 0.462 (p<0.001). Additionally, the coefficient for CHI_{my} is positive and significant, 0.003 (p<0.001), indicating that retailers tend to achieve higher sales when public health policies are more stringent. One potential explanation for this counterintuitive finding is that during periods of strict public health measures, government stimulus payments and financial assistance programs increase consumers' disposable income, enabling higher spending on durable goods such as furniture (Scopelliti 2021). Moreover, consumers spend less on services, such as travel and restaurant meals during this time, substituting spending on goods, such as furniture.

Table 4. Estimation Results – Poisson Regression Model

	Model 1.1 $SALES_{rmy}$	Model 1.2 $SALES_{rmy}$	Model 1.3 $SALES_{rmy}$	Model 1.4 $SALES_{rmy}$	Model 1.5 $SALES_{rmy}$
RM_PLAN_{rmy}	0.019*** (0.000)	1.291*** (0.001)	0.012*** (0.000)	0.008*** (0.000)	0.794*** (0.001)
AR_TECH_{rmy}	0.042*** (0.000)	0.046*** (0.000)	0.215*** (0.000)	0.028*** (0.000)	0.207*** (0.000)
ON_DSN_{rmy}	0.980*** (0.000)	0.978*** (0.000)	0.976*** (0.000)	1.129*** (0.000)	1.150*** (0.000)
RET_LEN_{rmy}	0.852*** (0.001)	1.003*** (0.001)	1.193*** (0.001)	0.647*** (0.001)	1.049*** (0.001)
RM_PLAN_{rmy}* RET_LEN_{rmy}		-0.555*** (0.000)			-0.347*** (0.000)
AR_TECH_{rmy} * RET_LEN_{rmy}			-0.071*** (0.000)		-0.073*** (0.000)
ON_DSN_{rmy} * RET_LEN_{rmy}				-0.083*** (0.000)	-0.098*** (0.000)
CHI_{my}	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
NUM_STR_{rmy}	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
FIR_AGE_{ry}	0.462*** (0.005)	0.462*** (0.005)	0.460*** (0.005)	0.450*** (0.005)	0.444*** (0.005)
Retailer fixed effect	Included	Included	Included	Included	Included
Month fixed effect	Included	Included	Included	Included	Included
Year fixed effect	Included	Included	Included	Included	Included
N	5,844	5,844	5,844	5,844	5,844
Chi square	significant	Significant	significant	Significant	significant

Notes: Robust standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

I conduct a scenario analysis to further explore the relationship between pre-sales and post-sales practices. Specifically, I examine the conditions under which these practices may act as substitutes or complements. Based on the results from Model 1.5, I predict sales performance across varying levels of return leniency (ranging from 1 to 5) and the availability of pre-sales practices, including room planner, AR tech, and online interior designer. The results of this analysis are presented in Table 5.

In the last column of Table 5, I report the differences in predicted sales between each scenario and the corresponding baseline scenario, where no pre-sales practices are implemented at each level of return leniency. At lower levels of return leniency, technology-based pre-sales and post-sales practices appear to be complementary, jointly enhancing sales performance. However, as return leniency increases, customers may rely less on room planner or AR tech when they feel protected by lenient return policies. This shift suggests a substitutive relationship between technology-based pre-sales and post-sales practices under high return leniency. On the other hand, the forecast indicates that retailers offering an online interior designer consistently achieve higher predicted sales compared to those without this human-based practice.

Table 5. Scenario Analysis – Predicted Sales

Pre-sales Practice	Return Leniency	Predicted Value	Difference
None	1	$ 51,953.27	
	2	$ 148,355.99	
	3	$ 423,636.05	
	4	$ 1,209,708.52	
	5	$ 3,454,367.74	
Room Planner	1	$ 81,261.69	$ 29,308.42
	2	$ 164,086.66	$ 15,730.67
	3	$ 331,333.27	$ (92,302.78)
	4	$ 669,040.58	$ (540,667.94)
	5	$ 1,350,965.39	$ (2,103,402.35)
AR Tech	1	$ 59,395.87	$ 7,442.60
	2	$ 157,616.48	$ 9,260.49
	3	$ 418,256.43	$ (5,379.62)
	4	$ 1,109,899.47	$ (99,809.06)
	5	$ 2,945,266.90	$ (509,100.84)
Online Interior Designer	1	$ 148,861.26	$ 96,907.99
	2	$ 385,524.49	$ 237,168.50
	3	$ 998,440.66	$ 574,804.61
	4	$ 2,585,785.79	$ 1,376,077.26
	5	$ 6,696,730.63	$ 3,242,362.89

To examine the robustness of my results, I employ a log-linear regression model as an additional check. The results, presented in Table 6, are consistent with those obtained from my main analysis, suggesting the robustness of my findings. Overall, my results demonstrate the effect of pre-sales and post-sales practices on sales performance and the substitutable relationship between the two types of policies. While each practice independently increases sales, the presence of pre-sales practices can substitute for post-sales practices (and vice versa).

Table 6. Estimation Results – Log-linear Regression Model

	Model 2.1 Ln($SALES_{rmy}$)	Model 2.2 Ln($SALES_{rmy}$)	Model 2.3 Ln($SALES_{rmy}$)	Model 2.4 Ln($SALES_{rmy}$)	Model 2.5 Ln($SALES_{rmy}$)
RM_PLAN_{rmy}	0.359*** (0.060)	0.671*** (0.076)	0.339*** (0.059)	0.335*** (0.059)	0.522*** (0.080)
AR_TECH_{rmy}	0.265*** (0.046)	0.253*** (0.046)	0.183*** (0.049)	0.249*** (0.046)	0.252*** (0.058)
ON_DSN_{rmy}	0.757*** (0.137)	0.778*** (0.136)	0.750*** (0.135)	1.103*** (0.138)	1.100*** (0.151)
RET_LEN_{rmy}	0.713*** (0.109)	0.829*** (0.109)	0.304** (0.113)	0.376*** (0.111)	0.481*** (0.120)
RM_PLAN_{rmy}* RET_LEN_{rmy}		-0.157*** (0.023)			-0.093*** (0.026)
AR_TECH_{rmy} * RET_LEN_{rmy}			-0.079*** (0.007)		-0.074*** (0.017)
ON_DSN_{rmy} * RET_LEN_{rmy}				-0.162*** (0.013)	-0.154*** (0.031)
CHI_{my}	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
NUM_STR_{rmy}	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
FIR_AGE_{ry}	0.131*** (0.013)	0.134*** (0.013)	0.131*** (0.013)	0.131*** (0.013)	0.133*** (0.013)
Retailer fixed effect	Included	Included	Included	Included	Included
Month fixed effect	Included	Included	Included	Included	Included
Year fixed effect	Included	Included	Included	Included	Included
N	5,844	5,844	5,844	5,844	5,844
F statistic	79.70***	78.75***	83.57***	84.51***	78.24***
R square	0.2263	0.2324	0.2432	0.2453	0.2472

Notes: Robust standard errors in parentheses. * p<0.05, **p<0.01, *** p<0.001.

5. Extended Analyses

To gain deeper insights into how pre-sales and post-sales practices influence sales performance, I conduct further analyses.

5.1. Five Factors of Return Leniency

I segmented return leniency into five factors, including time, monetary, effort, scope, and exchange. I explore the direct effect of these five factors, individually, and how they interact with pre-sales practices (room planner, AR tech, and online interior designer). I account for endogeneity as with the base models. The results of direct effect and moderating effect models are presented in Table 7 and Table 8 respectively.

In Table 7, the coefficients for TIM_LEN_{rmy}, MON_LEN_{rmy}, and EXC_LEN_{rmy} are positive and significant, 0.470 (p<0.001), 1.055 (p<0.001), and 0.113 (p<0.001), suggesting that offering longer return windows, full refunds, and cash refunds has a beneficial effect on retailer sales volume. In contrast, the coefficients for EFF_LEN_{rmy} and SCO_LEN_{rmy} are not significant, 0.511 (p>0.05) and -0.503

(p>0.05), indicating that eliminating the requirement for an original purchase receipt or making all products returnable does not have a significant impact on sales performance.

These findings highlight that consumers are especially sensitive to time- and money-related return policies, such as extended windows and full cash refunds, because these policies directly mitigate the fit risk from purchases. From a practical perspective, my results indicate that retailers aiming to boost sales might focus on return policies that reduce upfront risks by emphasizing extended time frames for returns and straightforward full refund options, rather than allocating resources to more complex or less salient policy enhancements that do not significantly drive purchase decisions.

Table 7. Estimation Results – Direct Effect of Five Factors

	Model 3.1 $SALES_{rmy}$	Model 3.2 $SALES_{rmy}$	Model 3.3 $SALES_{rmy}$	Model 3.4 $SALES_{rmy}$	Model 3.5 $SALES_{rmy}$
RM_PLAN_{rmy}	0.002*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.003*** (0.000)
AR_TECH_{rmy}	0.030*** (0.000)	0.038*** (0.000)	0.038*** (0.000)	0.038*** (0.000)	0.037*** (0.000)
ON_DSN_{rmy}	0.831*** (0.000)	0.890*** (0.000)	0.888*** (0.000)	0.888*** (0.000)	0.886*** (0.000)
TIM_LEN_{rmy}	0.470*** (0.000)				
MON_LEN_{rmy}		1.055*** (0.003)			
EFF_LEN_{rmy}			0.511 (0.873)		
SCO_LEN_{rmy}				-0.503 (0.479)	
EXC_LEN_{rmy}					0.113*** (0.001)
CHI_{my}	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
NUM_STR_{rmy}	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
FIR_AGE_{ry}	0.391*** (0.005)	0.420*** (0.006)	0.418*** (0.005)	0.417*** (0.005)	0.417*** (0.005)
Retailer fixed effect	Included	Included	Included	Included	Included
Month fixed effect	Included	Included	Included	Included	Included
Year fixed effect	Included	Included	Included	Included	Included
N	5,844	5,844	5,844	5,844	5,844
Chi square	significant	significant	significant	significant	significant

Notes: Robust standard errors in parentheses. * p<0.05, **p<0.01, *** p<0.001.

For the three significant post-sales factors, I analyze the moderating impacts of pre-sales practices. The results are presented in Table 8. The moderating effects of RM_PLAN_{rmy} are negative and significant across time, monetary and exchange return leniency, -0.154 (p<0.001), -0.227 (p<0.001), and -0.029 (p<0.001), indicating that this technology consistently diminishes the impact of return leniencies.

In contrast, the moderating effects of AR_TECH_{rmy} are inconsistent, negatively interacting with time leniency (-0.060, p<0.001) and exchange leniency (-0.000, p<0.001), while positively interacting with monetary leniency, (0.006, p<0.001). These results indicate customers may feel confident in their initial purchase decisions and have a clear expectation of product fit after using AR tech, reducing the need for time and exchange leniency. On the other hand, AR tech and monetary leniency together can drive higher sales performance. However, it should also be noted that AR tech is not widely employed by furniture retailers, so the results may be due to small numbers of observations.

ON_DSN_{rmy} also demonstrates inconsistent moderating effects, negatively interacting with time leniency (-0.058, p<0.001) and monetary leniency (-0.179, p<0.001), but positively interacting with exchange leniency (0.024, p<0.001). Thus, online designers may substitute for some aspects of return leniency but amplify the impact of others.

Table 8. Estimation Results – Moderating Effect of Significant Factors

	Model 4.1 $SALES_{rmy}$	Model 4.2 $SALES_{rmy}$	Model 4.3 $SALES_{rmy}$
RM_PLAN_{rmy}	0.051*** (0.000)	0.154*** (0.000)	0.031*** (0.001)
AR_TECH_{rmy}	0.029*** (0.000)	0.027*** (0.000)	0.038*** (0.000)
ON_DSN_{rmy}	0.837*** (0.000)	1.021*** (0.001)	0.863*** (0.002)
TIM_LEN_{rmy}	1.149*** (0.001)		
MON_LEN_{rmy}		4.629*** (0.013)	
EXC_LEN_{rmy}			0.830*** (0.045)
RM_PLAN_{rmy} * TIM_LEN_{rmy}	-0.154*** (0.000)		
AR_TECH_{rmy} * TIM_LEN_{rmy}	-0.060*** (0.000)		
ON_DSN_{rmy} * TIM_LEN_{rmy}	-0.058*** (0.000)		
RM_PLAN_{rmy} * MON_LEN_{rmy}		-0.227*** (0.000)	
AR_TECH_{rmy} * MON_LEN_{rmy}		0.006*** (0.000)	
ON_DSN_{rmy} * MON_LEN_{rmy}		-0.179*** (0.001)	
RM_PLAN_{rmy} * EXC_LEN_{rmy}			-0.029*** (0.001)
AR_TECH_{rmy} * EXC_LEN_{rmy}			-0.000*** (0.000)
ON_DSN_{rmy} * EXC_LEN_{rmy}			0.024*** (0.002)
CHI_{my}	0.002*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
NUM_STR_{rmy}	0.000*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
FIR_AGE_{ry}	0.391*** (0.005)	0.477*** (0.009)	0.418*** (0.005)
Retailer fixed effect	Included	Included	Included
Month fixed effect	Included	Included	Included
Year fixed effect	Included	Included	Included
N	5,844	5,844	5,844
Chi square	significant	significant	significant

Notes: Robust standard errors in parentheses. * p<0.05, **p<0.01, *** p<0.001.

5.2. Online and Offline Sales Performance

I extend my analysis to explore how pre-sales and post-sales practices influence online and offline sales channels, using the same models as employed in my base analysis. The results are presented in Table 9 and Table 10 for online sales and offline sales, respectively.

Since my results are consistent among all models, I use Model 5.1 and Model 5.5 in Table 9 to interpret the results for online sales performance. In Model 5.1, the coefficients for RM_PLAN_{rmy}, AR_TECH_{rmy}, and ON_DSN_{rmy} are positive and significant, 0.494 (p<0.001), 0.248 (p<0.001), and 0.045 (p<0.001), indicating that pre-sales practices (room planner, AR tech, and online interior designer) increase a retailer's online sales volume. In Model 5.5, the coefficient for $RM\_PLAN_{rmy} * RET\_LEN_{rmy}$ is positive and significant, 0.149 (p<0.001), suggesting that room planner amplifies the positive effect of return leniency on sales. In contrast, the coefficients for $AR\_TECH_{rmy} * RET\_LEN_{rmy}$ and $ON\_DSN_{rmy} * RET\_LEN_{rmy}$ are negative and significant, -0.304 (p<0.001) and -0.559 (p<0.001), implying that when AR tech and online designers are available, lenient return policies become less critical to boosting sales.

These findings underscore the importance of balancing pre-sales and post-sales practices in an online setting. While a lenient return policy can be a strong incentive for customers to complete their purchases, complementary pre-sales tools, such as room planner, may further enhance customer confidence, thus increasing sales. However, other innovative supports (e.g., AR tech and online designer) can substitute for the reassurance provided by return leniency, offering alternative avenues for customers to visualize and customize their potential purchases.

Table 9. Estimation Results – Online Sales

	Model 5.1 ON_SALES_{rmy}	Model 5.2 ON_SALES_{rmy}	Model 5.3 ON_SALES_{rmy}	Model 5.4 ON_SALES_{rmy}	Model 5.5 ON_SALES_{rmy}
RM_PLAN_{rmy}	0.494*** (0.001)	0.114*** (0.001)	0.495*** (0.001)	0.501*** (0.001)	0.115*** (0.001)
AR_TECH_{rmy}	0.248*** (0.000)	0.250*** (0.000)	0.265*** (0.005)	0.249*** (0.000)	0.903*** (0.005)
ON_DSN_{rmy}	0.045*** (0.000)	0.044*** (0.000)	0.045*** (0.000)	1.081*** (0.002)	1.244*** (0.002)
RET_LEN_{rmy}	0.716*** (0.001)	0.974*** (0.001)	0.717*** (0.001)	0.865*** (0.001)	1.187*** (0.002)
RM_PLAN_{rmy}* RET_LEN_{rmy}		0.144*** (0.000)			0.149*** (0.000)
AR_TECH_{rmy} * RET_LEN_{rmy}			-0.008*** (0.002)		-0.304*** (0.002)
ON_DSN_{rmy} * RET_LEN_{rmy}				-0.483*** (0.001)	-0.559*** (0.001)
CHI_{my}	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.006*** (0.000)
NUM_STR_{rmy}	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
FIR_AGE_{ry}	-0.186*** (0.006)	-0.161*** (0.006)	-0.186*** (0.006)	-0.189*** (0.006)	-0.166*** (0.006)
Retailer fixed effect	Included	Included	Included	Included	Included
Month fixed effect	Included	Included	Included	Included	Included
Year fixed effect	Included	Included	Included	Included	Included
N	4,540	4,540	4,540	4,540	4,540
Chi square	significant	Significant	significant	significant	significant

Notes: Robust standard errors in parentheses. * p<0.05, **p<0.01, *** p<0.001.

I use Model 6.1 and 6.5 to interpret results for offline sales performance. In Model 6.1, the coefficients for RM_PLAN_{rmy} and AR_TECH_{rmy} are positive and significant, 0.270 (p<0.001), and 0.642 (p<0.001), indicating that technology-based pre-sales practices (e.g., room planner and AR tech) are able to boost a retailer's offline sales volume. On the other hand, the coefficient for ON_DSN_{rmy} is negative and significant, -0.249 (p<0.001), implying that online designers are associated with fewer offline purchases, perhaps because they reduce the need for physical store visits.

Turning to Model 6.5, the coefficients for $RM\_PLAN_{rmy} * RET\_LEN_{rmy}$, $AR\_TECH_{rmy} * RET\_LEN_{rmy}$, and $ON\_DSN_{rmy} * RET\_LEN_{rmy}$ are negative and significant, -0.166 (p<0.001), -0.181 (p<0.001), and -0.140 (p<0.001). These findings suggest that once fit risk is mitigated through room planner and AR tech, the incremental advantage of post-sales practices (e.g., lenient return policies) for boosting offline sales diminishes. In other words, when customers feel more confident prior to purchase due to room planner and AR tech, they are less influenced by lenient return policies in an offline setting. In addition, a lenient return policy negatively moderates the relationship between online designer and offline sales performance. From a managerial perspective, retailers may need to adjust their investments in pre-sales and post-sales practices to strike an optimal balance between pre- and post-sales practices. By carefully coordinating these offerings, firms can cater to diverse customer preferences, ultimately strengthening their sales performance.

Table 10. Estimation Results – Offline Sales

	Model 6.1 OFF_SALES_{rmy}	Model 6.2 OFF_SALES_{rmy}	Model 6.3 OFF_SALES_{rmy}	Model 6.4 OFF_SALES_{rmy}	Model 6.5 OFF_SALES_{rmy}
RM_PLAN_{rmy}	0.270*** (0.000)	0.502*** (0.001)	0.270*** (0.000)	0.269*** (0.000)	0.668*** (0.001)
AR_TECH_{rmy}	0.642*** (0.000)	0.640*** (0.000)	0.556*** (0.002)	0.641*** (0.000)	1.076*** (0.002)
ON_DSN_{rmy}	-0.249*** (0.000)	-0.250*** (0.000)	-0.249*** (0.000)	0.024*** (0.001)	0.090*** (0.001)
RET_LEN_{rmy}	0.583*** (0.001)	0.553*** (0.001)	0.579*** (0.001)	0.587*** (0.001)	0.560*** (0.001)
RM_PLAN_{rmy}* RET_LEN_{rmy}		-0.096*** (0.000)			-0.166*** (0.000)
AR_TECH_{rmy} * RET_LEN_{rmy}			-0.035*** (0.001)		-0.181*** (0.001)
ON_DSN_{rmy} * RET_LEN_{rmy}				-0.112*** (0.000)	-0.140*** (0.000)
CHI_{my}	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
NUM_STR_{rmy}	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
FIR_AGE_{ry}	0.507*** (0.006)	0.507*** (0.006)	0.507*** (0.006)	0.507*** (0.006)	0.507*** (0.006)
Retailer fixed effect	Included	Included	Included	Included	Included
Month fixed effect	Included	Included	Included	Included	Included
Year fixed effect	Included	Included	Included	Included	Included
N	4,293	4,293	4,293	4,293	4,293
Chi square	significant	significant	Significant	significant	significant

Notes: Robust standard errors in parentheses. * p<0.05, **p<0.01, *** p<0.001.

6. Implications

This study analyzes the interplay between return leniency, room planner, AR tech, and online designers, focusing on their impact on retailer sales performance. This research offers several key theoretical contributions.

First, pre-sales fit risk mitigation practices serve as important diagnostic cues that effectively enhance retailer sales performance. My findings indicate that both technology-based and human-based pre-sales practices, including room planner, AR tech, and online designer, significantly boost retail online and total sales volumes. My analysis of offline sales reveals intriguing insights. Specifically, room planner and AR tech positively influence offline sales performance, suggesting that these technologies may encourage consumers to search for products online but complete their purchases in physical stores, a clear indication of webrooming behavior. Conversely, online human designers negatively impact offline sales, implying that these consultations guide consumers toward completing transactions online, reducing the likelihood of offline purchases.

Second, from a signaling perspective, my findings demonstrate that return leniency, as a post-sales fit risk recovery practice, enhances retail sales performance for both online and offline sales channels. Further analysis indicates that lenient policies related to time and monetary factors, such as length of return window, full refunds, and cash refunds, positively influence sales volumes. Conversely, lenient effort and scope return policies do not significantly impact sales performance, perhaps because a lower percentage of sales are impacted by these policies.

Finally, combining cue diagnosticity theory and signaling theory, I investigate how pre-sales (technology- and human-based) and post-sales (return leniency) practices may substitute or, in some cases, work together to boost sales performance. While existing studies, such as Gustafsson et al. (2021), Rao et al. (2018), and Wang et al. (2023), examine either pre-sales or post-sales practices in isolation, my findings demonstrate that the interplay between pre-sales practices (room planner, AR tech, and online designer) and post-sales practices (return leniency) is complex. These findings reveal how the substitution effects between pre-sales and post-sales practices depend on the specific mitigation practice. By jointly examining pre- and post-sales risk mitigation practices, I offer a comprehensive framework for understanding how retailers can strategically allocate resources to maximize sales performance.

My findings yield several managerial implications. First, although lenient return policies increase both online and offline sales volume, retailers may prioritize the most effective lenient return factors. Specifically, time, monetary and exchange leniency emerge as significantly beneficial to retailer sales performance. Therefore, retailers may consider investing in the extension of the timeframe for returns or weigh the benefits and costs of lenient monetary and exchange returns policies. In contrast, effort and scope leniency do not yield significant sales gains, although the costs of implementing these policies may also be low. By actively tracking the performance of each leniency factor, firms can allocate resources toward the most impactful policies, thereby maximizing both sales and customer satisfaction.

Second, retailers can focus on the interplay between post-sales practices (return policy) and pre-sales practices (room planner, AR tech, and online designer). My findings show that pre-sales practices can diminish consumer reliance on lenient return policies, while also increasing sales across both online and offline channels. This insight calls for a balanced investment strategy: retailers might rely less on highly lenient return policies in contexts where customers have access to advanced visual aids or professional consultations that reduce fit risk. At the same time, in markets or segments with limited technology adoption, lenient return options may remain a cornerstone of purchase confidence. By aligning pre-sales and post-sales efforts based on specific customer needs and purchase behaviors, firms can heighten their overall efficiency and enhance the sales performance.

Third, room planner and AR tech appear to boost both online and offline sales performance. By offering an immersive and interactive preview of how products fit with consumer needs, these technologies alleviate fit issues that hamper purchasing decisions. Retailers can integrate online trials with in-store experiences, for instance, by equipping sales associates with data on customers' virtual room designs or AR-generated product preferences. Multi-channel strategies may allow for a cohesive experience that bridges the online-offline divide, capitalizing on consumers' digital exploration and nudging them to complete transactions in physical outlets.

Overall, these insights highlight that there is no single approach to risk mitigation that works best across all channels. Instead, managers should assemble a nuanced portfolio of return policies, technology tools, and human services that align with their strategic priorities, whether that be driving online or offline sales.

7. Conclusion

This study examines the impact of pre-sales and post-sales practices on retailer sales performance, with a specific focus on their interaction in mitigating fit risk. My findings reveal that while technology-based and human-based pre-sales practices, such as room planner, AR tech, and online interior designer, help consumers reduce purchase hesitation, they do not fully eliminate the risk of misfit. Consequently, post-sales practices, particularly lenient return policies, remain a critical component in alleviating consumer concerns. However, my results suggest that the relationship between these two practices is contingent on the level of return leniency. When return policies are strict, pre-sales and post-sales practices act as complements, jointly enhancing sales performance. In contrast, under highly lenient return policies, they may act as substitutes, as the presence of one weakens the positive effect of the other.

By disaggregating return leniency into its five key dimensions, time, monetary, effort, scope, and exchange, I provide a nuanced understanding of the return leniency factors that significantly contribute to retail sales. My findings indicate that time, monetary, and exchange leniency enhance sales performance, while effort and scope leniency do not yield significant benefits. In addition, online interior designers play a unique role in the pre-sales phase by offering personalized guidance that can enhance sales.

This study makes several theoretical contributions. First, based on cue diagnosticity theory and signaling theory, I extend current research that views pre-sales and post-sales practices independently by revealing their substitutive effects. This finding refines existing literature on omnichannel retailing and consumer uncertainty reduction (Gustafsson et al. 2021; Hong and Pavlou 2014; Vidojevic 2024). Second, I highlight the evolving role of human expertise in online retail settings, demonstrating how online interior designers may serve as a proactive uncertainty reduction mechanism.

From a managerial perspective, my results suggest that retailers can strategically balance their investments in pre-sales and post-sales practices to improve sales performance. Specifically, while lenient return policies are effective at boosting sales, retailers can prioritize the most impactful return leniency factors, time, monetary, and exchange flexibility, while reconsidering the costs associated with other policies. Furthermore, retailers can leverage advanced visualization tools such as room planners and AR technology to reduce consumer reliance on return policies, particularly in online channels where fit risk may be most pronounced.

This study has several limitations that present opportunities for future research. First, I focus on retail sales volume rather than profitability. While sales volume is a critical performance indicator, profit margins may vary based on return costs, operational expenses, and pricing strategies. Future research could extend this analysis to examine how pre-sales and post-sales practices influence retail profitability. Second, although fit risk is particularly pronounced in the furniture industry due to product size, weight, and logistical constraints (Narvar Team 2021), it is also a significant challenge in other sectors, such as apparel. Future studies could explore whether the effects of pre-sales and post-sales practices differ across industries, providing insights into how industry-specific factors shape consumer decision-making. Third, while my findings suggest that pre-sales and post-sales practices may act as substitutes, the underlying causal mechanisms remain unclear. Future research could investigate whether consumers who utilize technology-based or human-driven pre-sales services develop greater confidence in their purchase decisions, leading to fewer returns, or whether other factors, such as price sensitivity, brand trust, or prior shopping experiences, mediate this relationship. Finally, this study focuses on room planners, AR tech, and online human designers as pre-sales practices, along with return leniency as a post-sales practice. However, retailers employ a variety of additional strategies to mitigate fit risk, including video consultations, live chat support, and in-home trial programs, that are not examined in this study. Future research could explore these alternative strategies to determine whether their effects align with or differ from the findings of this study, offering a more comprehensive understanding of how retailers can enhance the consumer shopping experience.

Summarization

This dissertation contributes to the understanding of retail technologies by examining their role in enhancing performance across different retail sectors. Drawing on interdisciplinary perspectives, I investigate how retail technologies influence consumer foot traffic and sales volume across diverse retail contexts, eyewear, grocery, and furniture. Each chapter offers unique theoretical insights and extends extant research streams in retail technology, channel management, consumer logistics, and fit risk mitigation.

The first chapter examines how virtual try-on (VTO) technology influences sales performance in the eyewear retail sector, particularly contrasting dual-channel and pure online retailers. This study contributes to the literature on customer-interfacing technologies (Grewal et al. 2020; Roggeveen and Sethuraman 2020) by shifting the focus from consumer adoption to firm-level outcomes, providing empirical evidence of VTO's impact on sales. This study also enhances understanding of channel capabilities by showing that VTO complements rather than substitutes for physical stores in dual-channel contexts (Avery et al. 2012), supporting the multichannel retailing literature. Furthermore, the study contributes to research on cross-channel behavior (Flavián et al. 2016; Jiao and Hu 2022), demonstrating how VTO encourages webrooming, browsing online and purchasing offline, thus promoting multichannel engagement and boosting overall sales resilience.

The second chapter examines the effects of mobile consumer scanning technology (MCST) in grocery retail, focusing on how shifting checkout from employees to consumers impacts store- and city-level outcomes. It contributes to the consumer logistics (CL) literature (Carbone et al. 2017; Wang et al. 2022) by showing how this shift influences behavioral and financial metrics such as dwell time, transaction size, visit frequency, and overall sales. Findings reveal a dual effect: while MCST lowers average spending per visit, it increases store traffic, ultimately boosting total sales. This highlights key tradeoffs in MCST adoption. The chapter also adds to research on retail mobile applications and MCST by moving from analytical analysis and consumer acceptance (Ferreira et al. 2023; Shi et al. 2021) to assess performance impacts. Finally, drawing on price transparency and mental accounting, the study shows that MCST encourages budget-conscious shopping by enabling real-time spending awareness (Ramanathan and Dhar 2010).

The third chapter investigates how pre-sales fit risk mitigation practices, such as room planners, augmented reality (AR), and online interior designers, interact with post-sales return leniency to influence furniture retailer sales performance. It contributes to the cue diagnosticity literature by showing that both technology- and human-based pre-sales practices serve as effective diagnostic cues, reducing fit uncertainty and boosting sales across channels. Interestingly, while room planner and AR tech drive offline purchases, online designers shift consumers toward online buying, adding nuance to cross-channel behavior. Second, drawing on signaling theory, the chapter shows that time, monetary, and exchange return leniency positively impact sales, while effort- and scope-based leniency have limited effect (Wang et al. 2024). Third, this study integrates cue diagnosticity and signaling theory to reveal how pre- and post-sales practices may be substitutes or complements. This integrative perspective offers a strategic framework for managing consumer fit risk.

Appendices

Appendix A: Table A1: List of Eyewear Companies in the Sample

Company	VTO	Dual Channel
America's Best	No	Yes
Coastal Contacts	Yes	No
Eye Safety Systems	No	No
EyeBuyDirect	Yes	No
Eyeconic	Yes	No
Eyeglass World	No	Yes
Felix Gray	Yes	No
Frames Direct	No	No
Garrett Leight	No	Yes
Glasses.com	No	No
GlassesUSA	Yes	No
Hubble Contacts	Yes	No
JINS	Yes	Yes
LensDirect	Yes	No
Lensabl	Yes	No
Lenscrafters	Yes	Yes
Liingo Eyewear	Yes	No
MOSCOT	Yes	Yes
My Eyelab	Yes	Yes
Oakley	No	Yes
Oliver Peoples	No	Yes
OptiContacts.com	Yes	No
Quay	Yes	Yes
Ray Ban	No	Yes
Solstice	Yes	Yes
Stanton Optical	Yes	Yes
Sunglass Hut	No	Yes
Target Optical	No	Yes
WALDO	Yes	No
Zenni Optical	Yes	No

Appendix B: Table A2: 1st Stage Estimation Results

	VIR_TRYON_{rwy}	VIR_TRYON_{rwy}*$DUAL\_CHANNEL_{rcwy}$
$CUM\_AR\_SEARCH_{cwy}$	0.000***	0.000***
	(0.000)	(0.000)
$DUAL\_CHANNEL_{rcwy}$	-0.003	-0.087***
	(0.018)	(0.015)
CHI_{cwy}	0.001***	-0.000***
	(0.000)	(0.000)
$CUM\_AR\_SEARCH_{cwy}$ *$DUAL\_CHANNEL_{rcwy}$	-0.000***	0.000***
	(0.000)	(0.000)
POP_{cy}	0.088+	0.142***
	(0.045)	(0.026)
$ANN\_CITY\_SALES_{rc,y-1}$	1.309***	0.245**
	(0.085)	(0.072)
Retailer City Fixed Effect	Included	Included
Year Fixed Effect	Included	Included
Month Fixed Effect	Included	Included
Model Statistic		
N	276,066	276,066
F Statistics	4124.03***	6576.00***

Notes: Robust standard errors in parentheses. + p<0.1, *p<0.05, ** p<0.01, *** p<0.001.

Appendix C: Identification of Triple Difference Term

Following Chen et al. (2023), in Equation (1), I initially assess the impact of VTO usage on online sales for pure online retailers with VTO, relative to pure online retailers without VTO, during the period of offline store closures. In Equation (2), I further assess the impact of VTO usage on online sales for dual-channel retailers with VTO, relative to the dual-channel retailers without VTO, within the same offline store closure period. Equation (3) introduces the triple-interaction measure, representing the difference between Equations (2) and (1). This metric quantifies the incremental online sales gain attributable to VTO usage for dual-channel retailers in comparison to pure online retailers, demonstrating VTO's encouragement of "reverse" webrooming effect.

Pure online retailers

$$\{E(ONLINE\_SALES_{rcwy}|V=1,D=0,N=1)-E(ONLINE\_SALES_{rcwy}|V=1,D=0,N=0)\}-$$
$$\{E(ONLINE\_SALES_{rcwy}|V=0,D=0,N=1)-E(ONLINE\_SALES_{rcwy}|V=0,D=0,N=0)\}$$
$$=\{(\beta_1+\beta_3+\beta_5)-(\beta_1)\}-\{(\beta_3)-(0)\}=\beta_5$$

Equation (1)

Dual-channel retailers

$$\{E(ONLINE\_SALES_{rcwy}|V=1,D=1,N=1)-E(ONLINE\_SALES_{rcwy}|V=1,D=1,N=0)\}-$$
$$\{E(ONLINE\_SALES_{rcwy}|V=0,D=1,N=1)-E(ONLINE\_SALES_{rcwy}|V=0,D=1,N=0)\}$$
$$=\{(\beta_1+\beta_2+\beta_3+\beta_4+\beta_5+\beta_6+\beta_7)-(\beta_1+\beta_2+\beta_4)\}-\{(\beta_2+\beta_3+\beta_6)-(\beta_2)\}=\beta_5+\beta_7$$

Equation (2)

Webrooming effect of VTO

$$[\{E(ONLINE\_SALES_{rcwy}|V=1,D=1,N=1)-E(ONLINE\_SALES_{rcwy}|V=1,D=1,N=0)\}-$$
$$\{E(ONLINE\_SALES_{rcwy}|V=0,D=1,N=1)-E(ONLINE\_SALES_{rcwy}|V=0,D=1,N=0)\}]-$$
$$[\{E(ONLINE\_SALES_{rcwy}|V=1,D=0,N=1)-E(ONLINE\_SALES_{rcwy}|V=1,D=0,N=0)\}-$$
$$\{E(ONLINE\_SALES_{rcwy}|V=0,D=0,N=1)-E(ONLINE\_SALES_{rcwy}|V=0,D=0,N=0)\}]$$
$$=\{(\beta_5+\beta_7)-(\beta_5)\}=\beta_7$$

Equation (3)

where V denotes VTO, D denotes Dual Channel, and N denotes Store Close.

Appendix D: Parallel Trends Test

The weighted stacked DID requires parallel trends assumptions for the estimated effects to have causal interpretations (Roth 2022). With the parallel trend assumption, the weighted stacked DID model enables me to identify dwell time, store visits, and transaction size due to the implementation of MCST.

I test the parallel trends assumption by using a relative time model. Following the approach of Torres-Reyna (2015), I create a vector of dummy variables for each month during the event windows of the pre-treatment periods. For example, in the estimations of store traffic and sales performance, $MONTH\_-1_m$ is equal to 1 in the first month prior to the implementation of Shop & Scan technology for both sub-experiments. Otherwise, it is equal to 0. Following this logic, $MONTH\_-2_m$ is equal to 1 two months prior to the treatment events and 0 otherwise, and so forth up to $MONTH\_-9_m$, the first month of pre-treatment windows. I then interact $SHOP\_SCAN_{se}$ with monthly dummy variables from $MONTH\_-8_m$ to $MONTH\_-1_m$ ($MONTH\_-9_m$ is not included due to perfect collinearity).

Table A3 and Table A4 show the results for the two store traffic measures and for the transaction size parallel trends tests. The p-values for all interaction terms are greater than 5%, suggesting the parallel trends are not significantly violated (at the 5% level) for these 3 estimations (Torres-Reyna 2015).

Table A3: Parallel Trends Assumption – Store Traffic

	Ln($DWEL\_TIME_{semy}$)	Ln($STOR\_VSIT_{semy}$)
$SHOP\_SCAN_{se}$	0.009 (0.008)	-0.004 (0.008)
$MONTH\_-1_m$	-0.110*** (0.015)	-0.064*** (0.014)
$MONTH\_-2_m$	0.039*** (0.010)	-0.053*** (0.012)
$MONTH\_-3_m$	0.018*** (0.004)	-0.021*** (0.004)
$MONTH\_-4_m$	0.102*** (0.011)	-0.051*** (0.014)
$MONTH\_-5_m$	0.128*** (0.009)	0.172*** (0.010)
$MONTH\_-6_m$	-0.007 (0.007)	-0.026** (0.009)
$MONTH\_-7_m$	-0.136*** (0.015)	-0.045** (0.016)
$MONTH\_-8_m$	0.054*** (0.012)	-0.074*** (0.015)
$SHOP\_SCAN_{se}$* $MONTH\_-1_m$	0.016+ (0.009)	-0.001 (0.010)
$SHOP\_SCAN_{se}$* $MONTH\_-2_m$	-0.007 (0.010)	0.010 (0.013)
$SHOP\_SCAN_{se}$* $MONTH\_-3_m$	0.007 (0.011)	0.004 (0.012)
$SHOP\_SCAN_{se}$* $MONTH\_-4_m$	-0.004 (0.012)	-0.000 (0.014)
$SHOP\_SCAN_{se}$* $MONTH\_-5_m$	0.002 (0.009)	-0.029+ (0.015)
$SHOP\_SCAN_{se}$* $MONTH\_-6_m$	-0.005 (0.009)	0.002 (0.013)
$SHOP\_SCAN_{se}$* $MONTH\_-7_m$	0.011 (0.009)	-0.016 (0.011)
$SHOP\_SCAN_{se}$* $MONTH\_-8_m$	-0.013 (0.009)	0.008 (0.011)
$AREA\_POP_{semy}$	0.005* (0.002)	-0.002 (0.003)
$AREA\_INCOME_{semy}$	0.000 (0.006)	-0.011 (0.007)
$AREA\_SIZE_{semy}$	-0.020** (0.006)	0.033* (0.014)
$SEN\_INX\_T_{my}$	0.027*** (0.003)	0.005+ (0.003)
Store fixed effect	Included	Included
Month fixed effect	Included	Included
N	1,602	1,602
F statistic	52.76***	117.13***
R square	0.5068	0.6130

Notes: Clustered standard errors in parentheses. +p<0.1, *p<0.05, **p<0.01, *** p<0.001.

Table A4: Parallel Trends Assumption – Transaction Size

	Ln($SIZE_{cemy}$)
$SHOP\_SCAN_{ce}$	-0.032 (0.069)
$MONTH\_\text{-}1_m$	0.120 (0.111)
$MONTH\_\text{-}2_m$	-0.002 (0.057)
$MONTH\_\text{-}3_m$	0.155 (0.110)
$MONTH\_\text{-}4_m$	-0.089 (0.097)
$MONTH\_\text{-}5_m$	0.074 (0.099)
$MONTH\_\text{-}6_m$	0.232+ (0.137)
$MONTH\_\text{-}7_m$	0.069 (0.109)
$MONTH\_\text{-}8_m$	0.114 (0.123)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}1_m$	-0.121 (0.084)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}2_m$	-0.033 (0.084)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}3_m$	-0.048 (0.086)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}4_m$	0.009 (0.086)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}5_m$	-0.002 (0.086)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}6_m$	0.015 (0.085)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}7_m$	0.063 (0.083)
$SHOP\_SCAN_{ce}$* $MONTH\_\text{-}8_m$	-0.015 (0.085)
CTY_POP_{cemy}	-0.624 (0.606)
CTY_INC_{cemy}	0.400 (0.280)
$SEN\_INX\_S_{cemy}$	0.007* (0.003)
City fixed effect	Included
Month fixed effect	Included
N	1,188
F statistic	11.18***
R square	0.1145

Notes: Clustered standard errors in parentheses. +p<0.1, *p<0.05, **p<0.01, *** p<0.001.

Appendix E: Robustness Check

When Meijer introduced its Shop & Scan program across its stores in Michigan, the expansion was implemented in waves based on regions, rather than on market-level or consumer-level characteristics. However, factors such as location could still influence the implementation decisions, causing potential endogeneity concerns. Therefore, following the methodology of Arpino and Cannas (2016), I conduct a robustness check using propensity score matching to better account for the impact of location characteristics on MCST implementation. This method allows for the matching of stores (city markets) between treatment and control groups that are similar across observed covariates, including population, income, and area size. The procedure contains two steps for each of my two datasets. In the first stage, I use the latent variable model proposed by Williams (2020) and estimate a logistic regression predicting the likelihood that an observation belongs to the treatment group as follows.

For the models that uses store-level traffic data, I estimate:

$$\begin{aligned} SHOP\_SCAN^{*}_{se} \quad &= \alpha_0 + \alpha_1 \cdot AREA\_POP_{semy} + \alpha_2 \cdot AREA\_INC_{semy} + \alpha_3 \cdot \\ &AREA\_SIZ_{semy} + \varepsilon_{se} \end{aligned}$$

$SHOP\_SCAN^{*}_{se}$ is a dichotomous variable that determines the treatment group membership, according to:

$$SHOP\_SCAN_{se} = \begin{cases} 1 \; if \; SHOP\_SCAN^{*}_{se} > 0 \\ 0 \qquad Otherwise \end{cases}$$

Next, for models that use city market-level data, I estimate:

$$SHOP\_SCAN^{*}_{ce} \quad = \alpha_0 + \alpha_1 \cdot CTY\_POP_{cemy} + \alpha_2 \cdot CTY\_INC_{cemy} + \varepsilon_{ce}$$

where

$$SHOP\_SCAN_{ce} = \begin{cases} 1 \; if \; SHOP\_SCAN_{ce}^{*} > 0 \\ 0 \qquad Otherwise \end{cases}$$

$SHOP\_SCAN_{se}$ or $SHOP\_SCAN_{ce}$ is equal to 1 if the observation is in the treatment group, and 0 otherwise, with subscript $s(c)$ denoting store (city) and e, the sub-experiment. The predicted values for $SHOP\_SCAN_{se}$ and $SHOP\_SCAN_{ce}$ are the propensity scores. These scores estimate the probability of an observation being assigned to the treatment group based on observable characteristics, thereby correcting for biases that arise from non-random assignment. Propensity score matching retains the treatment and control sample stores (cities) with closely matched propensity scores.

To estimate $SHOP\_SCAN_{se}(SHOP\_SCAN_{ce})$, I include demographic variables for city markets (Fisher et al. 2019). $AREA\_POP_{semy}(CTY\_POP_{cmy})$ is population size of a trade area (city) prior to the adoption of Shop & Scan program in that market. $AREA\_INC_{semy}(CTY\_INC_{cmy})$ represents the median income in a trade area (city). For the store traffic model, I add another city-market variable, $AREA\_SIZ_{semy}$, to measure the size of a trade area for a store in square miles.

To ensure treatment observations are matched with similar control observations, for both models, I retain the sample of observations with propensity scores for the treatment and control groups within an acceptable range (Datta et al. 2018). I use a nearest-neighbor matching method without replacement to determine the control group observations for both the foot traffic and sales datasets (Caliendo and Kopeinig 2008). I apply a caliper size 0.20 times the standard deviation of the propensity scores in the treatment and control groups (Xu et al. 2017). In addition, I conduct the Kolmogorov-Smirnov test for the treatment and control observations to check for similarities in variance of covariates. Based on the tests, I cannot reject the null hypothesis of equality of variances between the treatment and control group characteristics. Table A5 and Table A6 below report the mean values of the market-specific variables between treatment and control groups, before and after propensity score matching, for foot traffic and sales performance, respectively. Before propensity score matching, there are significant differences between treatment and control groups. After matching, these differences become insignificant.

Table A5: Sample Means of Matching Variables – Store Traffic

Variable	Unit	Before matching			After matching		
		Treatment	Control	t-statistics	Treatment	Control	t-statistics
$AREA\_POP_{semy}$	10,000 people	5.38	9.16	11.59***	5.99	6.62	0.85
$AREA\_INC_{semy}$	10,000 Dollar	4.79	5.37	9.41***	4.81	4.71	-0.83
$AREA\_SIZ_{semy}$	10 square miles	3.82	3.72	-1.42+	3.70	3.58	-0.60

Notes: + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

Table A6: Sample Means of Matching Variables – Sales Performance

Variable	Unit	Before matching			After matching		
		Treatment	Control	t-statistics	Treatment	Control	t-statistics
CTY_POP_{cemy}	10,000 people	3.05	3.97	1.51+	3.06	2.87	-0.06
CTY_INC_{cemy}	10,000 Dollar	5.54	4.02	-7.02***	5.54	5.09	-1.00

Notes: + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

The robustness check results after propensity score matching in Table A7 support my baseline results. Consistent with my base results, these models suggest the positive impact of Shop & Scan on store visits and negative impacts of the technology on dwell time and transaction size.

Table A7: Results after Propensity Score Matching

	$Ln(DWEL\_TIME_{semy})$	$Ln(STOR\_VSIT_{semy})$	$Ln(TRAN\_SIZE_{cemy})$
$SHOP\_SCAN_{se}$	0.014 (0.013)	0.046 (0.028)	
$SHOP\_SCAN_{ce}$			0.425 (0.260)
$POST_{emy}$	0.012 (0.014)	0.011 (0.021)	0.531+ (0.291)
$SHOP\_SCAN_{se}$* $POST_{emy}$	-0.033+ (0.017)	0.048+ (0.027)	
$SHOP\_SCAN_{ce}$* $POST_{emy}$			-0.541+ (0.296)
N	1,268	1,268	1,050
F statistic	4.43*	6.73***	11.35*
R square	0.0156	0.0540	0.0146

Notes: Robust standard errors in parentheses. + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

Appendix F: Extended Analyses

I conducted several additional analyses to gain deeper insights into the business value of MCST, focusing on: (1) origin of increased store visits, (2) changing shopping patterns, and (3) store sales.

Appendix F1: Origin of Increased Store Visits

First, although I find that MCST increases total store visits, it is unclear whether these increased visits are from new customers or repeat trips from existing customers. I explore the origin of increased visits by using number of unique customers, (NUM_CUST_{semy}), and average visits per customer, (AVG_VSIT_{semy}). Data on NUM_CUST_{semy} and AVG_VSIT_{semy} are collected from Placer.ai, and represent the count of unique customers and the mean value of visits per customer at store s in month m of year y in sub-experiment e. Consistent with my main model, I use weighted stacked DID and include all control variables to test my model. The results are reported in Table A8. The coefficients for $SHOP\_SCAN_{se} * POST_{emy}$ are positive and significant, 0.053 (p<0.001) and 0.011 (p<0.05), indicating that the implementation of MCST increases both number of unique customers and the average number of visits per customer. Thus, the increased store visits come from both larger customer base and more repeat visits.

Table A8: Results – Consumer Base and Store Visits

	Ln(NUM_CUST_{semy})	Ln(AVG_VSIT_{semy})
$SHOP\_SCAN_{se}$	0.009 (0.006)	-0.053*** (0.003)
$POST_{emy}$	0.062*** (0.005)	-0.070*** (0.003)
$SHOP\_SCAN_{se}*POST_{emy}$	0.053*** (0.008)	0.011* (0.005)
$AREA\_POP_{semy}$	-0.002** (0.001)	0.002 (0.002)
$AREA\_INC_{semy}$	0.011*** (0.002)	0.003 (0.004)
$AREA\_SIZ_{semy}$	0.003 (0.002)	-0.042*** (0.007)
$SEN\_INX\_T_{my}$	0.014*** (0.001)	-0.011*** (0.001)
Store fixed effect	Included	Included
Month fixed effect	Included	Included
N	2,658	2,658
F statistic	254.49***	210.17***
R square	0.6349	0.5425

Notes: Clustered standard errors in parentheses. + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

Appendix F2: Changing Shopping Patterns

A Meijer assistant store manager indicated that a shortage of labor is one reason why the firm adopted Shop & Scan. If the introduction of MCST changes shopping patterns, then labor staffing may need to be revisited. I investigate the impact of MCST on day-of-week visits. Specifically, store visits are divided by day of the week. MON_VSIT_{semy}, TUE_VSIT_{semy}, WED_VSIT_{semy}, THU_VSIT_{semy}, FRI_VSIT_{semy}, SAT_VSIT_{semy}, and SUN_VSIT_{semy} represent the counts of total customer visits from Monday to Sunday respectively at store s in month m of year y in sub-experiment e. These data are collected from Placer.ai. Results are reported in Table A9.

In Table A9, the coefficients are positive and significant for Monday and Sunday, while negative and significant for Tuesday, Thursday, Friday, and Saturday. Based on these results, MCST differentially impacts visits by day of the week. As a result, retailers may need to monitor and alter their staffing patterns once the technology has been introduced.

Table A9: Results – Store Visits during a Week

	Ln(MON_VSIT$_{semy}$)	Ln(TUE_VSIT$_{semy}$)	Ln(WED_VSIT$_{semy}$)	Ln(THU_VSIT$_{semy}$)	Ln(FRI_VSIT$_{semy}$)	Ln(SAT_VSIT$_{semy}$)	Ln(SUN_VSIT$_{semy}$)
SHOP_SCAN$_{se}$	-0.010*** (0.001)	0.006*** (0.001)	-0.002** (0.001)	0.009*** (0.001)	0.003** (0.001)	0.002* (0.001)	-0.009*** (0.001)
POST$_{emy}$	-0.005*** (0.000)	0.002*** (0.000)	-0.001* (0.000)	0.004*** (0.000)	0.001+ (0.000)	0.000 (0.000)	-0.002** (0.001)
SHOP_SCAN$_{se}$*POST$_{emy}$	0.014*** (0.002)	-0.007*** (0.001)	0.001 (0.001)	-0.011*** (0.001)	-0.003** (0.001)	-0.003* (0.001)	0.009*** (0.001)
AREA_POP$_{semy}$	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000+ (0.000)	-0.000 (0.000)	-0.000 (0.000)
AREA_INC$_{semy}$	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.001* (0.001)	-0.000 (0.000)	-0.001 (0.000)
AREA_SIZ$_{semy}$	0.001 (0.000)	-0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
SEN_INX_T$_{my}$	0.000*** (0.000)	-0.000* (0.000)	0.000 (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	0.000*** (0.000)
Store fixed effect	Included	Included	Included	Included	Included	Included	Included
Month fixed effect	Included	Included	Included	Included	Included	Included	Included
N	2658	2658	2658	2658	2658	2658	2658
F statistic	556.23***	352.44***	303.45***	375.94***	337.22***	365.82***	217.23***
R square	0.4461	0.5947	0.5812	0.6904	0.4623	0.6206	0.5614

Notes: Clustered standard errors in parentheses. + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

Appendix F3: Store Sales

MCST results in lower transaction sizes (reducing sales) but increases in store visits (increasing sales). I investigate the net effect from these offsetting measures to determine the impact of MCST on sales. Monthly, city market-level retail sales volumes for Meijer were collected from Earnest Analytics. The log values of sales volume, $Ln(SALES_{cemy})$, represents store sales volume in city c in month m of year y in sub-experiment e. Consistent with my main analyses, I apply a weighted stacked DID model and include all control variables to examine the impact of MCST on overall retailer sales performance.

The results from this analysis are reported in Table A10. The coefficient for $SHOP\_SCAN_{ce} * POST_{emy}$ is positive and significant, 0.060 (p<0.01), indicating that Shop & Scan increased Meijer's monthly sales volume by 6%. Therefore, the increase in store visits more than compensated for the reduced transaction size, ultimately increasing the retailer's sales.

Table A10: Results – Store Sales Volume

	$Ln(SALES_{cemy})$
$SHOP\_SCAN_{ce}$	0.023 (0.022)
$POST_{emy}$	-0.026+ (0.014)
$SHOP\_SCAN_{ce}* POST_{emy}$	0.060** (0.022)
CTY_POP_{cemy}	0.001 (0.001)
CTY_INC_{cemy}	-0.000 (0.002)
$SEN\_INX\_S_{my}$	-0.002 (0.004)
City fixed effect	Included
Month fixed effect	Included
N	1,980
F statistic	46.05***
R square	0.2921

Notes: Clustered standard errors in parentheses. + p<0.1, * p<0.05, **p<0.01, *** p<0.001.

Appendix G: Details of the First-stage Analysis

To analyze the effect of pre-sales and post-sales practices on retailers' sales performance, I use the average adoption of room planner, AR tech, online interior designer, and return leniency of other retailers (excluding focal retailer r) in month m of year y as our instruments. Firms often adopt successful practices of their competitors (Chen and MacMillan 1992; Porter 1980). Moreover, retailers may use unique practices to differentiate themselves from their rivals. Thus, other retailers' adoption of practices may positively or negatively affect focal retailer's adoption, satisfying the criteria in the use of instrumental variable regression.

The impact of competitor's adoption of pre-sales and post-sales practices on a focal retailer's sales is likely to be indirect, mediated by the retailer's own willingness to adopt such practices. Customers make purchasing decisions by extensively comparing the design support options or return policies across different retailers. They actively assess and weigh offerings such as pre-sales designing services and post-sales return leniency before finalizing their purchases (Brynjolfsson et al. 2013; Verhoef et al. 2015). This suggests that the influence of competitors' practices on a focal retailer's sales occurs through a comparison with the focal retailer's own offerings (Berman and Thelen 2004; Cao and Li 2015). Hence, while competitors' adoption of pre-sales and post-sales practices may shape customer expectations and influence a focal retailer's performance, this effect cannot be separated from the retailer's own adoption decisions. If competitors' enhanced practices attract more customers, it is likely because the focal retailer does not match or exceed those offerings.

In sum, competitors' adoption of pre-sale and post-sales practices should be correlated with focal retailer's adoption decision, but it should not be directly correlated with focal retailer's sales performance. Similar instrumental variables have been used in past studies, such as Brymer et al. (2024), Ghose et al. (2012), Hausman (1996), Paraskevas et al. (2024), and Petrin and Train (2010). I use a two-stage least squares (2SLS) model with the instrumental variable to estimate my model.

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